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# The Role of Business Information Visualization in Knowledge Creation

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## ABSTRACT

Past research suggests that one of the reasons causing Business Intelligence (BI) systems to fall short of expectations could be that certain BI capabilities may not be appropriate for individuals' or organizational challenges. Our research proposes the need to enhance our understanding of information and knowledge processes to address the issue. We evaluate the appropriateness of adopting the implications of information and knowledge processes to Business Information Visualization (BIV) as one of BI capabilities by exploring how data interaction and data representation reduce information-based challenges of uncertainty and complexity, thus enabling the creation of new insights. Formal model and resulting propositions are offered. Research implications suggest that effective and efficient insight generation can be achieved by deploying BI visualization capabilities only if those capabilities result in knowledge workers' perception of lower information uncertainty and complexity. Larger implications of this study for BI, BIV and knowledge creation process are discussed.

## Keywords

Business Information Visualization, Knowledge Management, Knowledge Creation, Insight, Business Intelligence, Information Uncertainty, Information Complexity

## INTRODUCTION

Business Information Visualization (BIV) or the use of technology capabilities to visualize business data (Tegarden 1999) has recently become a central focus for practitioners dealing with BI implementations. Given BI's promise of enablement of better and faster decision making (Gartner 2010a; Sharda, Barr and McDonnell 1988) the stakes are becoming high for companies to successfully deploy it (Jourdan, Rainer, and Marshall 2008), hence the importance of BIV is recognized by both researchers (Zhang 2001) and practitioners (Howson 2010).

BI systems represent an umbrella of technologies that subsumes decision support systems, executive information systems , and management information systems (Olszak and Ziemba 2007). Despite BI popularity, both practitioners (Gartner 2010b) and researchers (Sharda et al. 1988) report mixed results for BI implementations. BIV is also increasing in popular, but examples of misuse of BIV capabilities by BI vendors and users is being reported (Few 2010). There is a real potential that BIV will not meet expectations as was the case with other hyped BI capabilities. Given large investments in BI technologies, greater understanding of the conditions that enable BIV to more effectively meet its ever increasing expectations is critical. The goal of this research is to improve our understanding of those conditions and provide theoretical basis and a set of propositions for future empirical research.

Two related research streams inform this study. One stream of research suggests that one of the reasons for failures of decision making systems such as BI and BIV is that organizations sometimes use them in inappropriate contexts. To apply a technology capability to a particular problem, an organization first needs to recognize uncertainty, complexity, ambiguity and divergent understanding (Zack 2007). Consequently, organizations need to understand how particular capabilities support decision making based on the type of problem it is trying to solve. The second stream of research explores BI capabilities as a subset of Knowledge Management (KM) (Herschel and Jones 2005). Combined, these two literature streams imply that determining the role of BI and its BIV capabilities requires an understanding of the problem it is trying to solve first and foremost, which requires understanding of not only of data and information but also the underlying knowledge management processes such as knowledge creation (Zack 2007).

This research focuses on incorporating existing theoretical lenses from knowledge and information processing to increase our understanding how the use of BIV capabilities of BI systems supports knowledge workers' insight generation as a form of knowledge creation. Specifically this paper explores how two BIV capabilities, data interaction and data representation, reduce two information-based challenges of information uncertainty and information complexity, to facilitate knowledge creation.

## LITERATURE REVIEW

### Review of the Literature on Knowledge Management

In order to ensure the sustainability of organization's competitive advantage, firms need to be effective in mobilization of their knowledge resources (Holsapple and Joshi 2001). Knowledge has been defined as a justified belief that increases an entity's capacity for effective action (Huber 1991) and is often discussed using the continuum of data, information and knowledge (Grover and Davenport 2001). This view falls under knowledge vis-a-vis data and information knowledge perspective (Alavi and Leidner 2001) under which data is defined as facts or raw numbers, information is processed data and knowledge is personalized information. The distinction between explicit and implicit knowledge (Polanyi 1967) has also played an important role in KM research. Tacit knowledge is described as information in the mind of an individual that when articulated becomes explicit (Nonaka and Takeuchi, 1995). The interplay between tacit and explicit knowledge informs this research in terms of what predominant type of knowledge could and should be expected from a BI system – primarily knowledge in explicit form that when delivered effectively, through BIV capabilities, can generate insights allowing for support of tacit knowledge creation.

Various KM processes have been defined in the literature: knowledge generation (creation), knowledge codification, and knowledge transfer/realization (Alavi and Leidner 2001; Grover and Davenport 2001). Knowledge creation, as integral part of decision making, is of particular interest to this research. According to Grover and Davenport (2001) organizations often use data and information and attempt to add more value and create knowledge. Nonaka suggested the model of knowledge creation consisting of four modes: socialization, externalization, internalization, and combination (Nonaka 1994). Combination and internalization modes are of particular interest to this research as they offer a foundation for support of the notion that BI systems can serve (through combination mode) the role of explicit knowledge creation (Herschel and Jones 2005), as well as provide support for generation of insights (though internalization mode). This is consistent with existing research that suggests that BI can serve the supporting role in knowledge creation but only as an incremental process that builds on prior knowledge (Grover and Davenport 2001; Zack 2007).

The process of knowledge transformation/generation involves the creation of insight (Grover and Davenport 2001) and BI systems can be used to enhance the enabling conversion process supporting new knowledge creation. In Nemati, Steiger, Iyer and Herschel. (2002) relevant examples include Inductive Model Analysis System (IMAS) (Sharda and Steiger 1996) and case base reasoning (CBR) (Kolonder 1987). These systems use models as a form of explicit knowledge that can be used to create new inferences and insights. Others suggest a role for technology in knowledge creation through insight generation enabled by business models and technology/intelligence tools (Bolloju, Khalifa, and Turban 2002; Heinrichs and Lim 2005).

The KM literature supports three key conclusions relevant to this research (1) systems can generate explicit knowledge through its codification (2) the same systems can support generation of tacit knowledge by supporting incremental modification of existing mental models that manifests itself through knowledge workers' interpretations and pattern discovery, and (3) this incremental knowledge creation in the context of BI can be operationalized in terms of insights that are generated.

### Business Information Visualization

Information Visualization is "the use of computer-supported interactive visual representations of abstract data to amplify cognition" (Card, Mackinlay, and Shneiderman 1999, p.7). While there are many definitions of BIV (Tegarden, 1999), this paper adapts Card's definition to business data for three reasons: 1) it identifies the importance of interaction and representation capabilities , 2) emphasizes cognition as the relevant mechanism to enable decision making, and 3) has been widely adopted allowing for better inter-disciplinary alignment and integration.

Data representation (spatial representations that are derived from symbolic data) has been researched extensively and primarily focused on representation format or method in the form of understanding the impact of display choice between tabular and graphical representation (Cleveland 1985; Jarvenpaa and Dickson 1988). This research resulted in formulation of Cognitive Fit Theory, which suggests the importance of fit between the problem representation and the problem-solving task in achieving effective performance (Vessey 1991; Vessey and Galletta 1991). Keim (2002) termed data representation as visualization techniques and classified them as (i) standard 2D/3D displays (tables, bar charts, x-y plots), (ii) geometrically transformed displays (iii) icon-based displays (iv) dense pixel displays, and 5) stacked displays. Our research focuses on standard 2D/3D displays commonly found in BI.

Data interaction techniques are the capabilities that provide users with the ability to manipulate and interpret representations with the goal of providing better understanding (Ji Soo, Youn, Stasko, and Jacko 2007; Kosara, Bendix, and Hauser 2003). Older interaction taxonomies discuss seven interaction tasks: Overview, Zoom, Filter, Details-on-Demand, Relate, History, and Extract (Kosara et al. 2003). A more recent framework is organized around a user's intent (Select, Explore, Reconfigure, Encode, Abstract/Elaborate, Filter, and Connect) while interacting with a system (Ji Soo et al. 2007). Other relevant frameworks considered data interactions capabilities such as interactive reduction of the number of dimensions, user-driven filtering of data ranges and interactive hierarchy specification and proposed their usefulness through the mechanism of direct considerations of users' domain knowledge and exploration tasks during the preprocessing (Kreuseler and Schumann 2002).

Both data representation- and interaction-focused BIV research have the potential to improve decision performance and reduce information overload (Chervany and Dickson 1974; Chung, Chen and Nunamaker 2005). These effects are grounded in the capacity of BIV to appropriately align with human cognitive, perception and memory abilities (Baker, Jones and Burkman 2009). On the other hand, misunderstanding of those human abilities can result in poor design of BIV, resulting in opposite and often detrimental impact to effective decision making (Few 2004; Tufte 1990).

In summary, the literature informs us that (i) BIV is important aspect of BI/DSS systems (ii) data representation and interaction are essential to BIV (iii) BIV effects on information overload reduction are based on the research of human perception and cognition, and (iv) proper application of human perception and cognition research is essential in ensuring desired BIV effect.

#### BI Capabilities and Information Processing

We draw upon a model introduced by Zack (2007) that proposes the role of computer-supported decision making systems should be viewed as a problem of information and knowledge management (Figure 1). Zack suggests that organizations often implement KM and DSS in situations that may not be appropriate to their specific knowledge problems. He proposes that organizations face four unique challenges: (i) uncertainty (lack of information), (ii) complexity (amount of information causing difficulty in processing), (iii) ambiguity (lack of conceptual framework to interpret information) and (iv) equivocality (having competing conceptual frameworks). He associates first two challenges with information and the latter two with knowledge. Furthermore, he suggests a link between information and knowledge, where prior knowledge is required to be able to process information, which in turn would revise existing knowledge and in effect create new knowledge (Zack 2007).

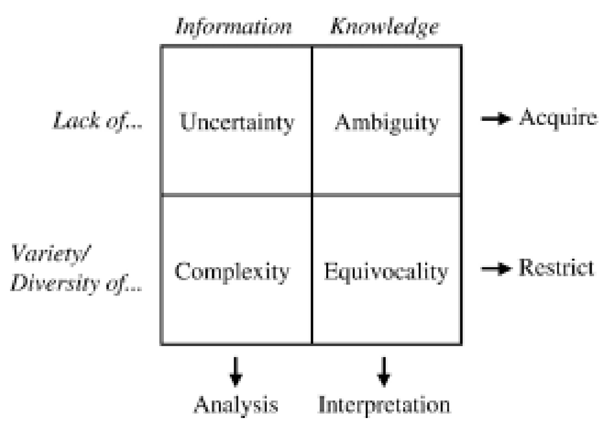


**Figure 1: Information and Knowledge Processing (Zack 2007)**

BI capabilities, such as BIV, are primarily effective in dealing with information processing and its two challenges – uncertainty and complexity. The mechanisms through which BIV capabilities of data interaction and data representation support this assertion are found in the hypotheses development section.

## RESEARCH MODEL AND PROPOSITION DEVELOPMENT

In this section we develop a research model (Figure 2) that incorporates key issues identified in our review of the literature. This model looks at the impact of two information visualization capabilities (Date Interaction and Data Representation on processing of Information Uncertainty and Information Complexity. The ability to process these information challenges is then tied incremental knowledge creation (operationalized as insight).

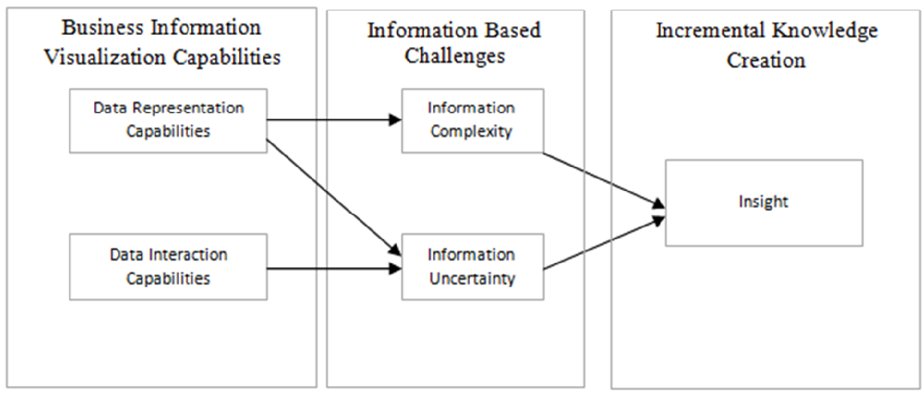


**Figure 2: Research Model**

### The effect of BIV's Data Representation Capabilities

Most visualization research focused on data representation is based upon theories of human perception and cognition. Miller (1956) describes human perceptual ability in terms of judgments about unidimensional and multidimensional stimuli. The ability to decode stimuli is prerequisite to visualization use (Cleveland 1985). This decoding process occurs in part due to visual perception abilities in which we exploit our visual channel inputs without creating an overload. Some of those well known exploitation mechanisms include Bertin's (1983) perceptual approaches (association, differentiation, ordered perception and quantitative perception), preattentive attributes (Treisman 1985), and Gestalt principles (Tufte 1983). Perceptual approaches describe various perceptual abilities and their link to understanding relationships between data (Baker et al. 2009; Bertin 1983). Preattentive attributes are features of the human visual system that allow certain data features (e.g., color, closure, orientation) to be perceived in a very short amount of time, unconsciously and without the need for serial search. Due to the existence of preattentive attributes, knowledge workers could identify, count and remember objects after having seen an image for only a fraction of a second – in other words, the process is virtually effortless and if applied as part of BIV is an effective mechanism to reduce information overload.

Baker, Jones et al.'s (2009) introduce the view in which cognition incorporates only post-perceptual processing of information such as internal representations and the role of human memory. Cognitive science suggests that users have internal representations of visualizations they see and that external representation should take this into consideration (Liu and Stasko 2010). The importance of memory when presenting and processing information visually is widely acknowledged (Bin and Watts 2010; Schmell and Umanath 1988) hence the use of design principles leveraging memory is well documented (Tegarden 1999). 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" has often been applied (Miller 1956; Tufte 1990). The choice of colors (Benbasat and Dexter 1986) and symbols (Bertin 1983) is often done in consultation with memory and cognition literature.

This research draws from above theories to suggest that through the same mechanism of amplified human perception and cognition, BIV can play significant role in enabling sensemaking (Baker et al. 2009). Since BIV representation layer is predominantly concerned with "amplification of cognition" (Card et al. 1999), by leveraging the mechanism of human cognition and perception it achieves, among other things, reduction in the information overload (IABC 2009; Tufte 1983). The reduction of information overload in the instance of Information Visualization is often associated with information complexity reduction (Harle, Neill and Padma 2008).

In summary, BIV capability of effective data representation leverages the mechanism of amplified human perception and cognition to reduce information overload and non-data noise (Tufte 1983), resulting in the perception of information complexity reduction. This suggestion of non-data clutter reduction, de-emphasis of less relevant and amplification of important data is in line with prior theoretical discussion of complexity reduction being achieved in BI through information restriction (Zack 2007).

P1. Data representation capability of the BI system reduces knowledge workers' experience of information complexity.

On the other hand, through the same mechanism of amplified human perception and cognition, best practices in information display (color, symbols, labels, layout, etc) can actually increase meaningful data, information and hidden meaning by providing clarity and as such act as additional information acquisition. Since the effect of information addition is associated with uncertainty reduction (Zack 2007), the relationship between data representation and information uncertainty is formulated such that:

P2. Data representation capability of the BI system reduces knowledge workers' information uncertainty.

### The Effect of BIV's Data Interaction Capabilities

In order to evaluate the impact of data interaction capabilities on information process of Information Uncertainty, we adopt the view that individuals in decision making context are often ask to make sense of information provided to them (Baker et al. 2009). This view is very similar to Uncertainty Reduction Theory (UCR) (Berger and Calabrese 1975) assertions that humans have an innate desire to predict and explain the world around them (Heisler and Crabill 2006). The theory suggests that the prediction and explanation of the world around them is enabled though interactions. In other words, the human condition of uncertainty avoidance motivates humans to interact with others, and the resulting outcomes of interactions enable subsequent uncertainty reduction (Berger and Calabrese 1975).

In business related decision making contexts, knowledge workers are faced with this issue. The motivation to reduce uncertainty is even greater in the workplace than in many social situations (Clampitt, Williams, and Korenak 2000). Typical business challenges include situations where knowledge workers' are asked to forecast next quarter's results, explain last year's results, and provide insights on how strategic changes will impact the bottom line. Knowledge workers are motivated and compensated to reduce the uncertainty around those answers and often seek to reduce uncertainty though discussions with coworkers or through the use of systems such as BI (Zack 2007).

While UCR theory is defined in terms of human-to-human interaction, others have noted the appropriateness of explaining Human Computer interactions though existing human to human-to-human theories. For example, research suggests that knowledge workers respond to technologies as though the technologies were social entities (Fogg and Nass 1997; Nass, Fogg and Moon 1996). This and other related AI research provides the needed support for ensuring the appropriateness of UTR implications on the relationship between BIV interaction capabilities and information uncertainty. This research provides the underlying mechanism that links data interaction capabilities with information uncertainty and results in our third proposition:

P3. Data interaction capability of the BI system reduces knowledge workers' perception of information uncertainty.

### The Effect of Information Processes on Insight

Appropriate matching of technology to problem and information processing mechanisms will increase decision making capabilities (Zack 2007). Both information acquisition and restriction within BI systems can impact information uncertainty and complexity in an attempt to enhance information processing. Through these mechanisms of information processes existing mental model/existing knowledge can be modified. In other words, through reduction of complexity and uncertainty, interpretation of the received information via BIV will alter the existing knowledge so that the next round of information can be interpreted in a new light and result in new knowledge (Zack 2007). Information and knowledge are tightly linked in a mutually interacting loop, and managing knowledge and learning requires managing information and the systems that provide it.

By combining the interplay between information and knowledge processes, the role of technology in support of that interplay, and KM literature suggests that knowledge created though BI systems is incremental and often experienced through generation of insight. Therefore, we propose:

P4. Information uncertainly negatively impacts knowledge workers' insight

P5. Information complexity negatively impacts knowledge workers' insight

Having established the mechanisms behind the relationships hypothesized by the model Figure re-introduces the final model with underlying mechanisms identified.

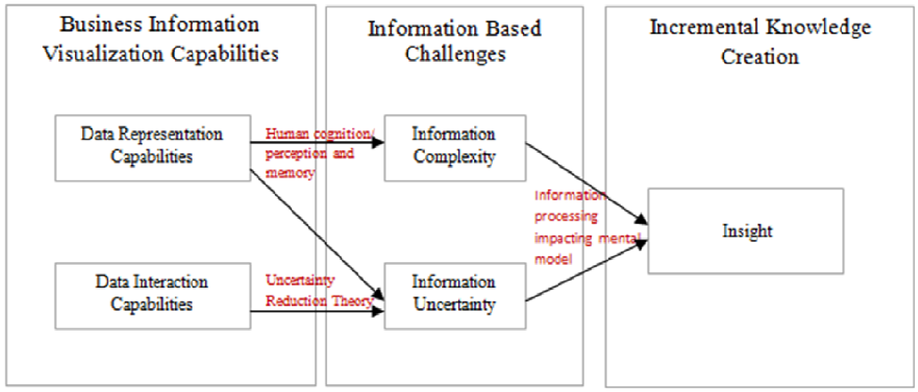


**Figure 4: Research Model with Relationship Mechanisms**

## DISCUSSION AND CONCLUSIONS

Our research suggests that understanding rooted in foundational information processes would allow for greater success of BI in decision making and have significant implications for understanding BI's BIV capabilities. To the best of our knowledge, no other research has applied this type of lens to the role of BIV and its capabilities. We offer a set of theoretically supported propositions aimed at improving our understanding of conditions under which BIV capabilities are effective in their support of knowledge creation.

Our theorizing has a number of implications. First, we suggest a more direct recognition of the role of knowledge to a) understand the limitations of BIV and BI, b) set more realistic expectations for the technology and c) assess individual and organizational challenges where BI technology is appropriate and those where it is not. This interplay of BI technology, information and knowledge continues to be problematic. For example, Herschel and Jones (2005) report finding from OTR consultancy claiming that 60% of consultants do not know the difference between knowledge management and BI, while at the same time some in the research community continue to think of KM as part of BI. These findings suggest that both practitioners and some in research community continue to approach and 'sell' BIV and BI at large as a solution for both data/information-based as well as knowledge-based challenges. This tendency to consider BI as the ultimate solution for decision making and the umbrella under which KM issues need to be addressed fails to properly account for implications of available research on KM process, knowledge creation and the implications of different types of knowledge. Even in instances when the difference between data/information and knowledge or between tacit and explicit knowledge is noted and interdependency between decision support systems and knowledge is recognized, the research in the respective fields (BI and KM) fail to adequately consider their integration (Bolloju et al. 2002). Building on Zack (2007), we reinforce that identification of the problem and its characteristics is crucial in BIV effectiveness. Hence, this study informs both practitioners and researchers that BIV should not be used for every type of problem and that BI should be viewed as part of KM and not the other way around. Our theorizing contributes to this discussion and offers a path for other researchers to adopt this lens when investigating the role of information, knowledge and technology in BI context.

Second, we highlight two specific BIV capabilities of data representation and data interaction as key in supporting knowledge workers' insight generation. While others have evaluated the effectiveness of those two capabilities in various contexts, this research is the first to integrate them into a conceptual process of knowledge creation. More specifically, the support of knowledge creation is only achieved if BIV tools reduce knowledge workers' perception of information uncertainty and complexity. Absent of that mediating effect, BIV capabilities will be unable to effectively support knowledge creation and, in the instances of particularly inappropriate representations and/or lack of interaction capabilities, may actually introduce unwanted ambiguity and equivocality in a problem that was originally contained within the information-based uncertainty and complexity sphere.

Third, the proposed research framework and resulting propositions are offered for empirical testing both at BIV and larger BI capabilities context. Potential enhancements and new model boundaries/conditions may emerge to further enhance our theorizing.

Fourth, vendors and practitioners can benefit from this research by having greater understanding how BIV supports user knowledge creation. Specific features of BIV capabilities could be evaluated on their effectiveness against information uncertainty and complexity; hence both implementation of BIV capable systems and release of features could be prioritized and rationalized.

In conclusion, our theorizing suggests that reduction in information uncertainty and information complexity is key to applying BIV to decision-making and knowledge creation. Within the BIV context, the two capabilities of data representation and data interaction are identified as important antecedents of information uncertainty and complexity. The mechanism behind those relationships is rooted in theories of human perception, cognition and uncertainty reduction. We encourage other researchers to continue the exploration of identified relationships for further enhancement and confirmation of our model and, ultimately, relevant adoption of resulting principles by the practice.

## REFERENCES

1. Alavi, M., and Leidner, D.E. (2001) Review: Knowledge Management and Knowledge Management Systems: Conceptual Foundations and Research Issues, *MIS Quarterly,* 25, 1, 107-136.
2. Baker, J., Jones, D.R., and Burkman, J. (2009) Using Visual Representations of Data to Enhance Sensemaking in Data Exploration Tasks, *Journal of the Association for Information Systems,* 10,7, 533-559.
3. Benbasat, I., and Dexter, A.S. (1986) An Investigation of the Effectiveness of Color and Graphical Information Presentation under Varying Time Constraints, *MIS Quarterly*, 10, 1, 59-83.
4. Berger, C.R., and Calabrese, R.J. (1975) Some Explorations in Initial Interaction and Beyond: Toward a Developmental Theory of Interpersonal Communication, *Human Communication Research,* 1, 2, 99-112.
5. Bertin, J. (1983) English Translation: Semiology of Graphics, University of Wisconsin Press, Madison, Wisconsin.
6. Bin, Z., and Watts, S.A. (2010) Visualization of Network Concepts: The Impact of Working Memory Capacity Differences," *Information Systems Research*, 21, 2, 327-344.
7. Bolloju, N., Khalifa, M., and Turban, E. (2002) Integrating Knowledge Management into Enterprise Environments for the Next Generation Decision Support, *Decision Support Systems,* 33, 2, 163-176.
8. Card, S., Mackinlay, J., and Shneiderman, B. (1999) Readings in Information Visualization: Using Vision to Think, Morgan Kaufmann Publishers.
9. Chervany, N.L., and Dickson, G.W. (1974) An Experimental Evaluation of Information Overload in a Production Environment, *Management Science,* 20, 10, 1335-1344.
10. Chung, W., Chen, H., and Nunamaker, J.F. (2005) A Visual Framework for Knowledge Discovery on the Web: An Empirical Study of Business Intelligence Exploration, *Journal of Management Information Systems,* 21, 4, Spring 2005, 57-84.
11. Clampitt, P., Williams, M.L., and Korenak, A. (2000) Managing Organizational Uncertainty: Conceptualization and Measurement, *Proceedings of the 50th annual conference of the International Communication Association*. Acapulco.
12. Cleveland, W.S. (1985) The Elements of Graphing Data, Wadsworth, Monterey, CA.
13. Davis, G., Benbasat, I., Dexter, A.S., and Todd, P. (1986) An Experimental Program Investigating Color-Enhanced and Graphical Information Presentation: An Integration of the Findings, *Communications of the ACM*, 29, 11, 1094-1105.
14. Few, S. (2004) Show Me the Numbers, Analytics Press, Oakland, CA.
15. Few, S. (2010) BI Has Hit the Wall, Retrieved 1/3/2011, from http://www.perceptualedge.com/blog/?p=820
16. Fogg, B.J., and Nass, C. (1997) Silicon Sycophants: The Effects of Computers That Flatter, *International Journal of Human-Computer Studies,* 46, 5, 551-561.
17. Gartner. (2010a) Gartner Says Treat Business Intelligence Programmes as Cultural Transformation, Not Just Another It Project, Retrieved 12/29/2010, from http://www.gartner.com/it/page.jsp?id=1490914
18. Gartner. (2010b) Gartner Outline the Top 10 Forces to Impact Outsourcing and IT Services Industry, Retrieved 12/29/2010, from http://www.gartner.com/it/page.jsp?id=1433214
19. Grover, V., and Davenport, T.H. (2001) General Perspectives on Knowledge Management: Fostering a Research Agenda, *Journal of Management Information Systems,* 18,1, Summer 2001, 5-21.
20. Hamming, R.W. (1962) Numerical Methods for Scientists and Engineers, McGraw-Hill, New York, NY.

21. Harle, C., Neill, D., and Padma, R. (2008) An Information Visualization Approach to Classification and Assessment of Diabetes Risk in Primary Care, *Proceedings of the 3rd INFORMS Workshop on Data Mining and Health Informatics*, D.A. J. Li, R. Sikora (ed.), 1-6.
22. Heinrichs, J.H., and Lim, J.-S. (2005) Model for Organizational Knowledge Creation and Strategic Use of Information, *Journal of the American Society for Information Science & Technology*, 56, 6, 620-629.
23. Heisler, J.M., and Crabill, S.L. (2006) Who Are "Stinkybug" and "Packerfan4"? Email Pseudonyms and Participants' Perceptions of Demography, Productivity, and Personality, *Journal of Computer-Mediated Communication*, 12, 1, 114-135.
24. Herschel, R.T., and Jones, N.E. (2005) Knowledge Management and Business Intelligence: The Importance of Integration, *Journal of Knowledge Management*, 9, 4, pp. 45-55.
25. Holsapple, C.W., and Joshi, K.D. (2001) Organizational Knowledge Resources, *Decision Support Systems,* 31,1, 39-54
26. Howson, C. (2010) Advanced Visualization Moves to Top of Mind at TDWI, BI Scorecard.
27. Huber, G.P. (1991) Organizational Learning: The Contributing Processes and the Literatures, *Organization Science,* 2, 1, 88-115.
28. IABC. (2009) "IABC Publishes Report to Help Members Prepare Messages for Information Overload Environments." Retrieved 12/11/2011, from http://news.iabc.com/index.php?s=43&item=201
29. Jarvenpaa, S.L., and Dickson, G.W. (1988) Graphics and Managerial Decision Making: Research-Based Guidelines, *Communications of the ACM*, 31, 6, 764-774.
30. Ji Soo, Y., Youn ah, K., Stasko, J.T., and Jacko, J.A. (2007) Toward a Deeper Understanding of the Role of Interaction in Information Visualization, *Visualization and Computer Graphics, IEEE Transactions on,* 13, 6, 1224-1231.
31. Jourdan, Z., Rainer, R.K., and Marshall, T.E. (2008) Business Intelligence: An Analysis of the Literature, *Information Systems Management* 25, 2, Spring2008, 121-131.
32. Keim, D.A. (2002) Information Visualization and Visual Data Mining, *Visualization and Computer Graphics, IEEE Transactions on,* 8, 1, 1-8.
33. Kolonder, J.L. (1987) Extended Problem Solver Capabilities through Case-Based Inference, *Proceedings of a Workshop on Case-Based Reasoning*, 176-181.
34. Kosara, R., Bendix, F., and Hauser, H. (2006) Parallel Sets: Interactive Exploration and Visual Analysis of Categorical Data, *Visualization and Computer Graphics, IEEE Transactions on,* 12, 4, 558-568.
35. Kosara, R., Hauser, H., and Gresh, D. (2003) An Interaction View on Information Visualization, EUROGRAPHICS
36. Kosslyn, S. (1989) Understanding Charts and Graphs, *Applied Cognitive Psychology,* 3, 185-225.
37. Kreuseler, M., and Schumann, H. (2002) A Flexible Approach for Visual Data Mining, *Visualization and Computer Graphics, IEEE Transactions on,* 8, 1, 39-51.
38. Liu, Z., and Stasko, J.T. (2010) Mental *Models, Visual Reasoning and Interaction in Information Visualization: A Top-Down Perspective*, *Visualization and Computer Graphics, IEEE Transactions on*, 16, 6, 999-1008.
39. Miller, G.A. (1956) The Magical Number Seven, Plus or Minus Two: Some Limits on Our Capacity for Processing Information, *Psychological Review,* 63, 2, 81-97.
40. Nass, C., Fogg, B.J., and Moon, Y. (1996) Can Computers Be Teammates?, *International Journal of Human-Computer Studies*, 45, 6, 669-678.
41. Nemati, H.R., Steiger, D.M., Iyer, L.S., and Herschel, R.T. (2002) Knowledge Warehouse: An Architectural Integration of Knowledge Management, Decision Support, Artificial Intelligence and Data Warehousing, *Decision Support Systems* 33, 2, 143-161.
42. Nonaka, I. (1994) A Dynamic Theory of Organizational Knowledge Creation, Organization Science, 5, 1, 14-37.
43. Nonaka, I., and Takeuchi, H. (1995) The Knowledge-Creating Company: How Japanese Companies Create the Dynamics of Innovation. Oxford University Press, New York, NY
44. Olszak, C.M., and Ziemba, E. (2007) Approach to Building and Implementing Business Intelligence Systems, *Interdisciplinary Journal of Information, Knowledge and Management*, 2, 135-149.
45. Polanyi, M. (1967) The Tacit Dimension. Routledge and Keoan Paul, London

46. Schmell, R.W., and Umanath, N.S. (1988) An Experimental Evaluation of the Impact of Data Display Format on Recall Performance, *Communications of the ACM,* 31, 5, 562-570.
47. Sharda, R., Barr, S.H., and McDonnell, J.C. (1988) *Decision Support System Effectiveness: A Review and an Empirical Test*, *Management Science,* 34, 2, 139-159.
48. Sharda, R., and Steiger, D.M. (1996) Inductive Model Analysis Systems: Enhancing Model Analysis in Decision Support Systems, *Information Systems Research* 7, 3, 328-341.
49. Tegarden, D.P. (1999) Business Information Visualization, *Communications of AIS*, 1, 4, 1-37.
50. Tractinsky, N., and Meyer, J. (1999) Chartjunk or Goldgraph? Effects of Presentation Objectives and Content Desirability on Information Presentation, *MIS Quarterly,* 23, 3, 397-420.
51. Treisman, A. (1985) Preattentive Processing in Vision, *Computer Vision, Graphics, and Image Processing,* 31, 156-177.
52. Tufte, E.R. (1983) The Visual Display of Quantitative Information. Graphics Press, Cheshire, CT
53. Tufte, E.R. (1990) Envisioning Information. Graphics Press, Cheshire, CT.
54. Vessey, I. (1991) Cognitive Fit: A Theory-Based Analysis of the Graphs Vs. Tables Literature, *Decision Sciences,* 22, 219-241.
55. Vessey, I., and Galletta, D. (1991) Cognitive Fit: An Empirical Study of Information Acquisition, *Information Systems Research,* 2, 1, 63-84.
56. Ware, C. (2000), Information Visualization: Perception for Design. Morgan Kaufmann, San Francisco, CA
57. Zack, M.H. (2007) The Role of Decision Support Systems in an Indeterminate World, *Decision Support Systems*, 43, 4, 1664-1674.
58. Zhang, P. (2001) Business Information Visualization: Guidance for Research and Practice, Encyclopedia of Microcomputers.