US-China Education Review A 7 (2011) 910-925
Earlier title: US-China Education Review, ISSN 1548-6613

Learning From Balance Sheet Visualization*

Uthai Tanlamai, Oranuj Soongswang
Chulalongkorn University, Bangkok, Thailand

This exploratory study examines alternative visuals and their effect on the level of learning of balance sheet users. Executive and regular classes of graduate students majoring in information technology in business were asked to evaluate the extent of acceptance and enhanced capability of these alternative visuals toward their learning performances. Adapting from the cognitive fit theory, higher level of learning performance will be achieved, if the type of visual representation matches the information processing requirement of the type of task activity. Results from 54% of the response rate of 104 students showed that the majority of respondents had visual-oriented learning style. Regardless of whichever type of task activity was performed, the respondents seemed to accept certain types of balance sheet visual more than the others. Mixture of number and graph was chosen as the most acceptable, then spatial table, and finally traditional graph. No statistical significant relationship was found between visual-task preferences and the respondents' learning performance.

Keywords: balance sheet, visualization, learning style, cognitive fit

Introduction

The increase in the computational power of modern computers has made the representation of data through graphs, charts or pictures easier and faster. Thus, visualization of business reports has received greater attentions from information system scholars. When an organization is small and its operations are not as complex, formal business reports may not be as important, because communication among a few users can be done verbally. By adding one or two users into the system, the communication links can climb up the exponential curve very quickly. Therefore, tables, graphs and charts are often used to represent a vast amount of complex numerical data, and spreadsheet visuals have become a de facto standard in business.

With many stakeholders involved, business reports can be grouped by their respective requirements. Internal users may want reports with different content from external users. Even different individuals within the same user group may need the information presented in different formats depending upon their cognition and learning capabilities. Huang, Chen, Guo, Xu, Wu, and Chen (2006) have reviewed the cognitive fit theory and argued that the value of representing data in visual form will lead to an effective and efficient way of understanding a large amount of data. However, what format the data should represent depends on the kind of task that the person is working on (Huang et al., 2006).

* **Acknowledgement:** The authors wish to acknowledge the research support from the Chulalongkorn University Centenary Academic Development Project and Chulalongkorn Business School. Helpful comments and suggestions from the reviewers and attendants of the 2009 Annual Meeting of the American Accounting Association in New York are greatly appreciated. Our special thanks go to the respondents for their kind cooperation and valuable inputs in providing information for this study.

Uthai Tanlamai, Ph.D., professor, Department of Accountancy, Chulalongkorn Business School, Chulalongkorn University.
Oranuj Soongswang, D.B.A., assistant professor, Department of Accountancy, Chulalongkorn Business School, Chulalongkorn University.

Also, the grouping of business reports into their functional use, financial performances and non-financial performances, and lends itself to representing the subsequent reports differently. In practice, however, it is challenging to find the criteria used to separate these two types of reports. Figure 1 depicts a two-by-two scheme of classifying business reports with some examples of typical reports used in business by different stakeholder groups.

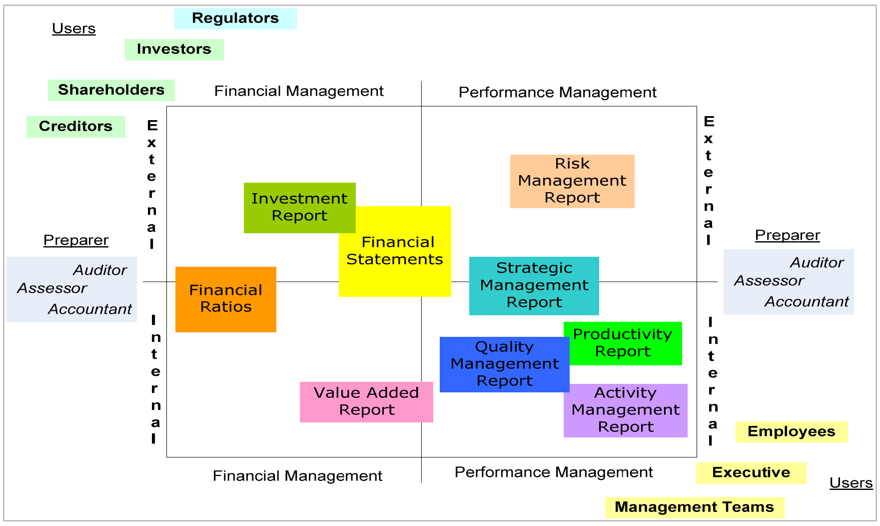


Figure 1. Classification of business reports.

The fact that organizations tend to provide the "one visual fits all" type of reports may not be as efficient or as effective in the stakeholders performing their respective tasks. Thus, the objective of this study is to add to the body of knowledge based on the individual's cognitive differences on business report visualization. It is argued that reports with data augmented by appropriate visuals will affect the efficiency and effectiveness of an individual's learning outcomes, and subsequently, his/her decision-making processes. With many types of business reports in use, the focus of this exploratory research is only on financial report visualization, since these reports appear to be ubiquitous to all users.

The contents and forms of financial reports have been scrutinized by both theorists and practitioners for a long time. For example, the "new reporting models for business" study from the "information for better markets" series carried out by the ICAEW (Institute of Chartered Accountants in England and Wales) examines the concepts of reporting financial performance (ICAEW, 2003). The study reviews 11 models used to solve financial reporting problems, such as serving multiple stakeholders, meeting decision-making needs, accounting for intangibles, achieving transparencies in business reporting, and so on. One of the solution models deals with the concern about relevancy and usefulness of business reports. Here, a unified business report with ten components was recommended by Jenkins who chaired the development taskforce in 1991 and was later elected to be the Chairman of the US Financial Accounting Standards Board. The Jenkins Report (1994; revised 1995) suggested disclosure of financial and non-financial data and its management analysis as well as forward-looking information on top of the information about management, shareholders and detailed background of the company. With similar concerns about the lack of disclosing non-financial performance, Kaplan and Norton (2001) offered the balanced scorecard model (1992; revised 1996) to report business performance from four perspectives.

In the same report were reviews of other models including, for example, the “Tomorrow’s Company Report” (1995; revised 1998), “The 21st Century Annual Report” (1998) and “Sustainability Reporting Guidelines” (2000; revised 2002). Many of these models were proposed in order to get businesses to produce reports that would reflect the relationships between different groups of stakeholders. Building public trust from ValueReporting™ (2001; revised 2002) was also proposed so that the valid, transparent and real financial position of the firm could be reported promptly at all times (ICAEW, 2003). It should be noted that although much has been said about the contents and processes of reporting business performance, hardly any of the proposed models consider the visualization aspect of these reports. It is argued here that report visualization can augment the usefulness of content and enhance many desirable features of reports as specified in those proposed models. The basic question asked in this study is what kind of visuals will fit with the information processing tasks of financial report users and whether these visuals can affect their learning performance.

Types of Visuals and Visualization

Spatial and temporal dimensions are the most typical criteria used in taxonomy development. Within spatial dimensions, there can be unlimited numbers of classification schemes depending on the perspectives or theories employed. In the research notes on multi-dimensional visuals for data mining, Sachinopoulou (2001, p. 27) classified the data mining tools that lend themselves to the types of visual being produced, for example, geometric technique[1], icon technique[2], hierarchical technique[3], distortion technique in three dimensional space[4], and two and three dimension graphs. Scatter-plot and matrices were found to take less time for learning than other visuals like tree or other basic graphs. To position glyphs, Ward (2002) classified the placement strategy according to the characteristics of data (raw or derived data) and to the structural characteristics of placement (sequential, hierarchical or network).

With a different conceptualization, Thomson, Hetzler, MacEachren, Gahegan, and Pavel (2005) proposed the typology of visualizing uncertainty. The uncertainty is caused by factors, such as granularity of data, data collection method, data processing, transformation, distribution or communication processes. All these factors can affect the way users would perceive the uncertainty and reliability of data, especially when the source of data is from a personal report or person-to-person communication. To reduce the uncertainty, one can try to obtain data from different sources, and cross-check the assumption of each data source. The author suggests a framework used to differentiate visuals for metadata and makes reference to the work of Butternfield and Beard (1994) who classified data into discrete, categorical and continuous data where the quality of data is important. Visual characteristics that are useful to cognition are as follows: accuracy/error, precision, completeness, consistency, lineage, currency/timing, credibility, subjectivity and interrelatedness. Ward (2002) also reviewed the work of Gershon (1994) in his book about the cause of imperfect knowledge. The argument for the cause of imperfection is the insufficient, incomplete, incoherent uncertain, complex and inadequate presentation of data,

[1] Geometric techniques use coordinates to construct visuals based on geographical space, including techniques, such as (1) plots and matrices; (2) hyperslice; (3) prosection views; (4) surface plots, volume plots, contours; (5) parallel coordinates; and (6) textures and rasters.

[2] Icon techniques are known as data representation as: (1) stick figure; (2) chernoff faces; (3) color icon; (4) autoglyph; and (5) glyphs.

[3] Hierarchical displays are: (1) hierarchical axes; (2) dimension stacking; (3) trees (tree maps, cone tree); (4) worlds within worlds; and (5) info cube.

[4] Distortion techniques used in business applications are: (1) perspective wall; (2) pivot table and table lens; and (3) hyperbolic trees.

resulting in incomplete knowledge (Thomson et al., 2005).

To represent scientific data, many efforts have been made to represent the N-Dimensional data with 2D (2 Dimension) or 3D (3 Dimension). One example of this is the use of spherical self-organizing feature maps to represent the visuals of many years of snow falls on a surface map of different parts on earth (Sangole & Knopf, 2002). In order to discover knowledge through data-mining techniques, different types of visuals are used, for example, representing time series data with the cluster method, spiral method, or viztree method (Lin, Keogh, & Lonardi, 2005). Perhaps, one of the most effective applications of using 2D and 3D representation of vast amounts of data is the use of a periodic table of visualization methods (Lengler & Eppler, 2008). This is an interesting visual, since it incorporates color, abbreviations, icons, and even short text messages. As displayed in the Website, layers responding to mouse movement are added with corresponding picture files for each individual visualization method depicted. A combination of six classes of methods with three pairs of method attributes (process and structure, overview and detail, and convergent and divergent thinking) has made the representations quite complex, but the innovative use of the familiar periodic table concept simplifies the interpretation of the data. The six methods include data visualization, information visualization, concept visualization, strategy visualization, metaphor visualization and compound visualization.

The topology of visualization can keep on expanding, if we link those in science, social science and humanity together. In the latest work by Buckhard (2005), a framework of knowledge visualization within the knowledge management context is offered. The framework was based on concepts derived from the research into individual perception, specifically visual information processing in both bottom-up (direct perception) and top-down (constructive perception) dimensions. The framework was employed by the author and his associate to develop a new type of visual, project tube maps, to be used as an alternative to the familiar Gantt chart. A pilot study was done to test whether this alternative visual would be accepted by the users who are managers, students and employees in large organizations. They found that the users of the project tube maps were more effective in performing their work than the Gantt chart users (Buckhard & Stott, 2005). This is because the alternative visual can trigger the interests of users who appear to have a better understanding of how to manage the entire project. However, the Gantt chart was still found to better represent the structure and the timeline for each project task.

Visualization in the Business Reporting Environment

The recent business information system applications, BI (business intelligence) in particular, have incorporated visualization techniques extensively in their presentation of analytic results. A geographical information system that focuses on the transformation of symbolic data into spatial information has also been integrated into the BI applications quite seamlessly. The visuals used to represent a vast amount of complex business data can help enterprise users be more confident in making their decisions (Gonzales, 2004). Note that visualization research in business disciplines deals with people and how they see things. Thus, it is inevitable that business visualization must take into account social and psychological constructs, such as cognition, decision-making performance and other factors relating to human information processing.

Though much has been said about the benefits of visualization (Ufelder, 2000), especially in scientific inquiry (Borner, Chen, & Boyack, 2003), there are quite a few studies that report the role of graphs, charts, multidimensional depictions, and even the use of virtual reality in business and management area (Benbasat & Dexter, 1986; Cormier-Chisholm, 2002; Eve, 1984; Lee & Maclachlan, 1986; Potts, 1975; Venkata, 1985).

Also, there are different ways of utilizing visualization in business applications, for example, for modeling stakeholders (Fassin, 2008), for evaluating the pros and cons of alternatives and the prioritization of a user's needs from multiple criteria (Anderson & Krathwohl, 2001), for risk mapping (Ceniceros, 1998; Leibs, 2002) and visualization of cash-flow statements (Cole, 2003). Visualizations enable better sense-making and faster understanding of business information. Visual data enables our brain to be stimulated, thus, the retrieval of data from our short- and long- term memory can be quicker.

Computer-generated charts and graphs have been used to augment texts and numbers, since the very beginning, because they are efficient and effective representations of business information (Eve, 1984; Potts, 1975; Roa, 1985). After the proliferation of personal computers and the sharp taking off of spreadsheet software in early 1980s, visualization research started to receive attention as well, especially in the area of the effect of using 3D pictures in management tasks. There are many studies being conducted on when to use tables and when to use graphs. These studies have variations in the use of different graph types and the manipulation of patterns and colors (Few, 2004). Geographical information systems that used to be in the domain of scientific research have also been seen more and more in business research (Benbasat & Dexter, 1986; Dennis & Carte, 1998; Lee & Maclachlan, 1986).

Although visualization appears to be very useful in business operations, some would argue that there are too many visuals in today's media, advertisement and public communications. Sadler-Trainor (2005) pointed out that these visual overdoses can downplay the creative thinking process. He argued that textual data requires more brain activity. When texts are read, the brain will have to create an image or mental model of some kind and through this process, the brain will be constantly stimulated—a good training for creative thinking.

Research on the usability of products/services is similar to the studies on the usefulness of information, both deals with the need to satisfy users' requirements (Dumas & Redish, 1999; Rubin, 1994; Taggart & Tharp, 1977). An overly-designed information system might end up with more functionality than a user's needs, or produce excessive reports that may never be used. As Ackoff (1967) pointed out in his classic article, more is not always better. Managers might not always know what they want when being questioned by an information system designer. Thus, in many cases, the designer tends to put some buffers in his design. For example, having all possible types of graph available, providing subtotals at every level of calculation even though only a single total number is adequate and adding so many customized routines or spreadsheet macros that any software-upgrade means having to redo everything from the start. The fact that a computer processor can process the work very quickly might not help a manager at all. This is because it will take time to scrutinize and extract what might be needed from the vast amount of detailed data, graphs and charts being produced. Even though a manager gets the information he/she needs, there is no guarantee that a better decision can be made, since the process itself is very complex and the system might not be able to produce the needed information at every step along the way.

Decision-makers tend to use past experience and spatial inference to understand the decision-making environment. Visualization can trigger the ability to use metaphor to see the links among different system components of the same abstract domain. However, the spatial reference of individuals varies, because they have different perceptual or cognitive biases. Visualization can bring an individual's attention to the salient characteristics of information without much concentration. Also, visual representation of data can increase the efficiency in decision-making performance. Visuals, such as graphs and charts, will give a spatial perspective that could trigger the thought process to generate better insights to a problem domain.

Business visualization research has long been focused on decision-making performance and has not considered the user's learning performance. This line of research assumes the success of an information system to be synonymous with intention or the use of the system itself. However, information usage may or may not promote or enhance the learning capability of the information user. Starting with knowledge, users can move up to a higher level of the learning process, from just remembering to understanding and applying. A learned user should be able to analyze and synthesize as well as evaluate and eventually be able to create new knowledge or new procedures (N. Andrienko & G. Andrienko, 2003).

Cognition and Visualization

Individuals differ in their cognitive processes and their spatial visualizing capability. Zimowski and Weothke (1986) assembled examples of spatial test items and used them to examine variation in spatial visualizing abilities. The authors differentiated two types of information processing ability, analogy ability of structural visualization and the non-analog ability of verbal analytic reasoning. They found the former to involve holistic gestalt-like processing of visuo-spatial information and the latter to test general intelligence and verbal processing abilities. Both of these two spatial problem-solving techniques are quite common in critical thinking research where different strands of research exist to study human reasoning and mental model construction (Johnson-Laird, 1998) and the link between performance and thinking styles (Kim, Grimm, & Markman, 2007; Talbot, 1989).

Mixed findings have been reported on the effect of using tables versus graphs on decision-making performance (Benbasat & Dexter, 1986; Vessey, 1991, 1994). Sometimes, the use of tables results in better decision-making and other times graphs are better. This line of research examines the information-processing tasks as important factors that influence the cognitive fit of decision makers. It is argued that the type of information-processing task must fit the type of data representation (Vessey, 1991). For unstructured problems where innovative ideas are needed to reach alternative solutions, Stoyanov and Kirschner (2007) found student subjects who have the cognitive style of an "innovator" type to be able to generate novel ideas more than an "adaptor" type. By arguing that an individual's decision performance depends on the matching data representation and the information processing tasks required, Vessey (1991) in her landmark article proposed the cognitive fit theory. She classified information representation and the information processing tasks into two types: spatial and symbolic. The cognitive fit occurs, if the task type is spatial and the decision-maker is given visuals with spatial data representation.

Outcome-Based Learning

In general, the definition of "learning" is quite broad. The learning process allows one to acquire experience and expertise from performing a given task again and again. The experience gained will help a person develop higher-level learning, for example, greater understanding and better insight. A measurement of different levels of learning performance is known as outcome-based learning. Based on the work of Bloom (1956), there are six levels of learning. As shown in Table 1, different terms are used to describe the aims or outcomes of different levels of learning that, in turn, relate to the cognitive domain of a person (D' Andrea, 2003). Although these terms can serve as a good guideline to differentiate one level of learning from another, careful consideration must be given to test the reliability and validity of these measurements.

It is apparent that learning-style research relates closely to visualization. Felder and Silverman (1988) proposed the definition of learning style and for years tested the measurements of this construct in different contexts. As seen in Figure 2, the authors and their colleagues have changed some of the sub-constructs so as to keep up with the on-going changes in the business environment. The four original dimensions are active/reflective, sensing/intuitive, visual/verbal and inductive/deductive. As seen in Figure 2, a decade later, Felder and Solomon (1998) replaced the dimension of inductive/deductive with the sequential/global to keep up with the advent of digital and on-line communications. ILS (index of learning styles) was developed and distributed on-line, consisting of 11 questions for each dimension. Students are believed to learn better if the instructional design is aligned with their learning styles and cognitive processes. Students with a visually-oriented learning style were found to prefer the use of visual representation over verbal representation, and all active learners in his study were visual learners (Moallem, 2007/2008). Also, students with a high visual-learning style tended to rate lecture-based instruction as less beneficial to their learning performances.

Table 1

Level of Learning, Cognitive Domain, and Outcomes

Levels of learning	Aims/outcomes	Cognitive domain
Evaluation	Know/distinguish between	Judge, appraise, evaluate, compare, assess
Synthesis	Understand/choose	Design, organize, formulate, propose
Analysis	Determine/assemble	Distinguish, analyze, calculate, test, inspect
Application	Appreciate/adjust	Apply, use, demonstrate, illustrate, practice
Comprehension	Grasp/identify	Describe, explain, discuss, recognize
Knowledge	Become familiar/solve, apply, list	Define, list, name, recall, record

Note. Source: Adapt from Table 3.3 & 3.4, (p. 35) in D' Andrea (2003).

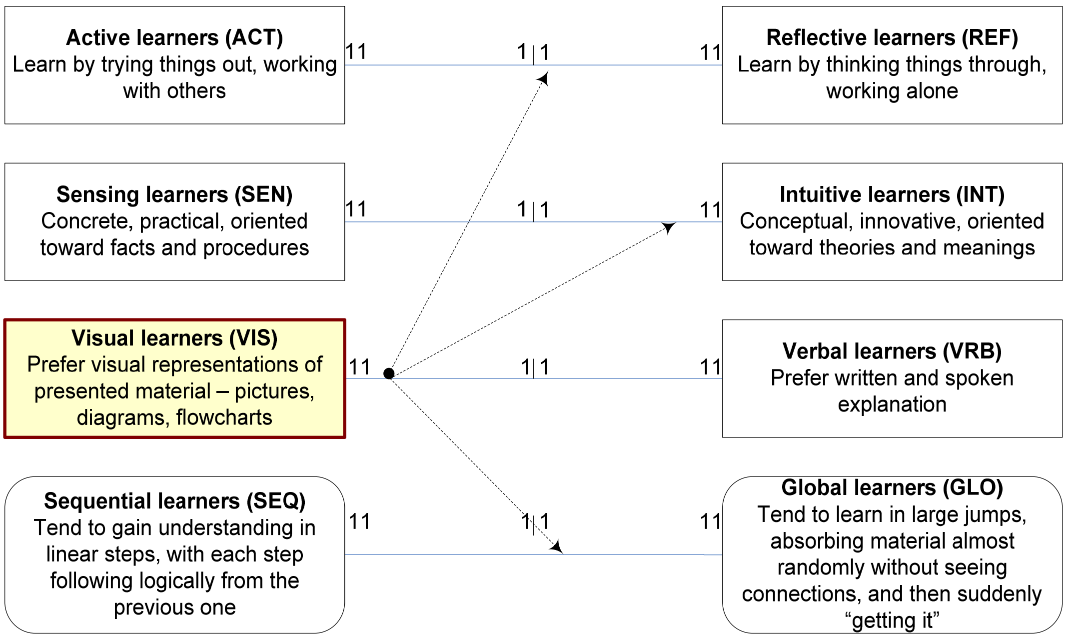


Figure 2. Felder's learning style.

The review of the literature above suggests that visualization research in the business setting needs to address a fundamental issue as to whether or not the way the information being presented will fit the information processing tasks of users. It is likely that report users may be able to achieve a higher level of learning, if they receive information that fits their way of thinking. Thus, information system designers are left with a challenging task of coming up with the visuals that are familiar, meaningful and thought-provoking such that new insights can come to various report users.

The present research framework for balance sheet visualization is drawn from the cognitive fit theory and learning outcome literature. The two main constructs of interest are perceived-learning performance and visual-task-fitting preference. Types of task activity and types of balance sheet visual are included as the antecedent variables to the visual-task-fitting preference construct. Learning style is included as a control variable, since individuals with a visually-oriented style are likely to prefer processing visual data than those who are more verbally-oriented.

In this exploratory research, the research framework examines whether there is a fit of a mental model while processing information of a given task activity using a certain type of balance sheet visual. Thus, the first hypothesis is stated as follows.

Hypothesis 1: There is no difference in users' visual-task-fitting preference among different types of balance sheet visuals.

In the information processing literature, decision makers are likely to make a better decision, if they receive the right information in the right format using appropriate visuals. Based on a similar rationale, balance sheet users may be able to achieve a higher learning level when exposed to visuals that fit with the types of task activities. Thus, the second hypothesis is stated as follows.

Hypothesis 2: There is no relationship between users' visual-task-fitting preference and their perceived-learning performance.

Research Method

Sampling frame and data collection a questionnaire was developed for on-line responses through a survey using the learning management system of the university. Two groups of graduate students in the Master of Science program in MSIT (information technology in business programs) from a large university in Thailand were employed for convenience purposes. The first group was the executive class of 56 students who had to have at least three years of working experience prior to entering into the program and the majority was still working while taking classes concurrently. The second group was the regular class, comprising 48 students who were not required to have any working experience prior to entering into this full-time program. However, some of these regular students did have work experience. The two groups had taken accounting and finance classes and were familiar with the concept and use of a balance sheet. Table 2 shows the profile of respondents.

Survey Instrument

To develop the data collection instrument, the authors developed a Web-based survey file and made the file available for students to download and upload from the university-wide LMS (learning management system) called blackboard. The system facilitates two-way communication between instructor and student. The study subjects were instructed to return the completed survey file by posting it on their class's LMS. No incentive was offered for participation. The Web-based survey was used so that colors and shapes of the visuals could be seen easily. The balance sheet visuals included were designed to be static with no drilled-down capability. This is to mimic the paper-based balance sheets that are widely used in a typical business setting in Thailand.

Ten alternative visuals were included. Some have been developed anew using a simple graphic design concept and the symbolic versus spatial representation of content. Others have been adapted from books and internet sources. All questions with alternative visuals were examined against the original symbolic representation that is spreadsheet table of texts and numbers. Among all ten alternative visuals, four are spatial tables, two are mixed of numbers and graphs and four are spatial graphs. Spatial tables were developed to give summary numbers with their corresponding proportions in an unorthodox table format. The two mixed visuals contain detailed numbers in traditional table and graph together formats. Finally, the spatial graphs are traditional column and bar charts produced by spreadsheet software. The visual samples are shown in Figure 3.

Table 2
Profile of Respondents

Respondent's characteristics	Group#1: Executive class (N1 = 56)	Group#2: Regular class [a] (N2 = 48)	Total number of respondents (N = 104)
With work experience	56 (100%)	31 (60.8%)	93 (82.3%)
Gender (male, female)	51.6%, 48.4%	43.1%, 56.9%	47.8%, 52.2%
Major (MIS, AIS, SIT) [b]	77.4%, 21.0%, 1.6%	60.8%, 25.5%, 13.7%	69.9%, 23.0%, 7.1%

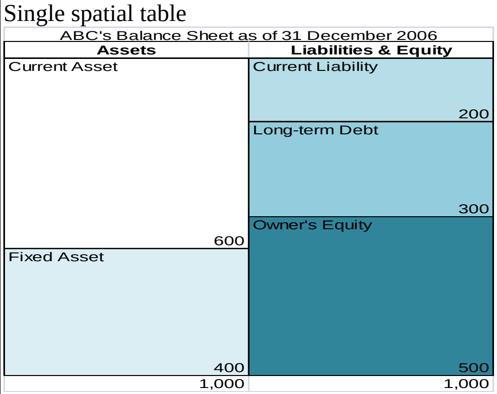
Notes. [a] Since the survey was voluntary, some students chose not to participate: 90.3% for Group#1 and 94.1% for Group#2. However, only 62 out of 104 students (54.9%) completed the survey that was usable for the analysis of relationships under study.
[b] The MSIT program has three majors: MIS (Management Information Systems), AIS (Accounting Information Systems) and SIT (Statistical Information Systems). For their undergraduate degree, many MIS students have backgrounds in engineering and biosciences, AIS in accounting and SIT in statistics.

Measurements

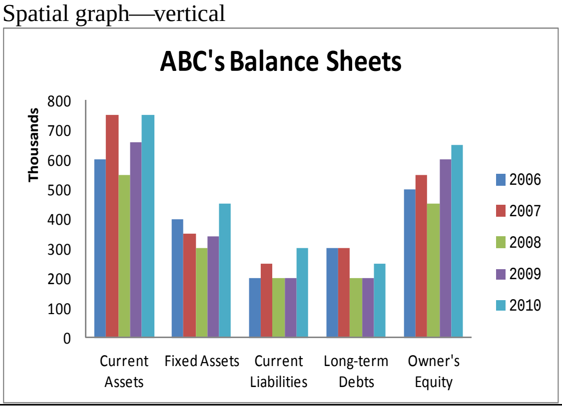
A 7-point Likert scale was used to assess the level of preference to a given visual and the level of learning one perceived from the task activity that he/she would perform. Multiple measures were used for each of the two main constructs and one moderating variable as follows.

Visual-task-fitting preference. The match between task activity and visual representation was measured by the level of preference a respondent indicated when determining a particular visual. It is expected that the higher the level of preference the greater the match or the fit. Four types of task activities that are typically performed by a balance sheet user include confirmation, review, understanding and decision. Table 3 shows the hypothetical match or fit between the type of task activity and the type of visual representation.

1 Single spatial table

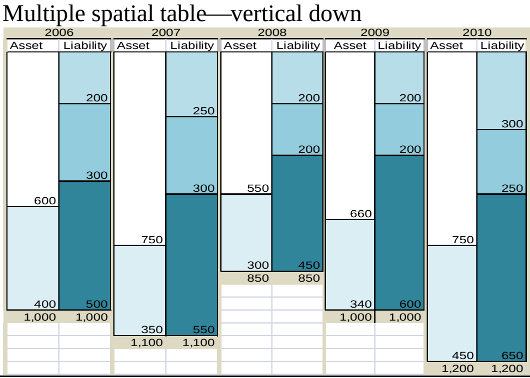


6 Spatial graph—vertical

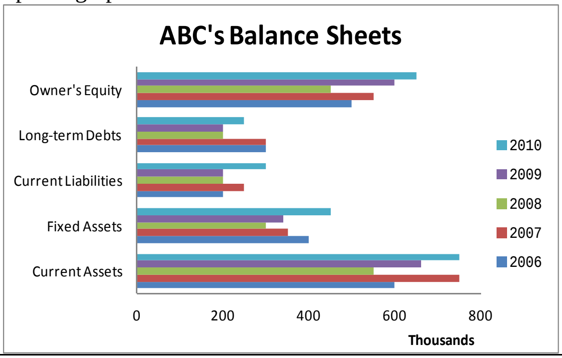


(to be continued)

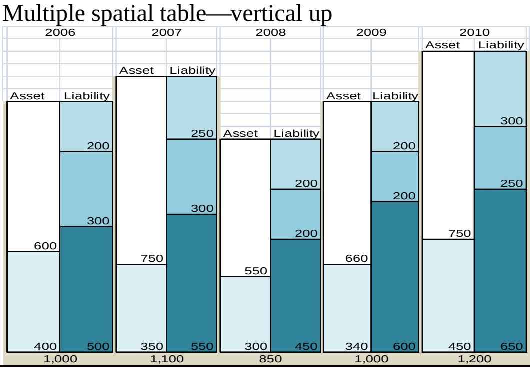
2 Multiple spatial table—vertical down



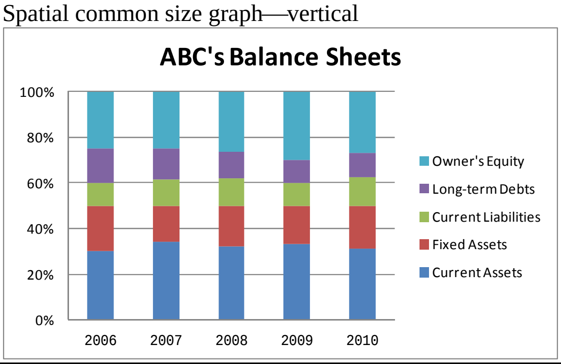
7 Spatial graph—horizontal



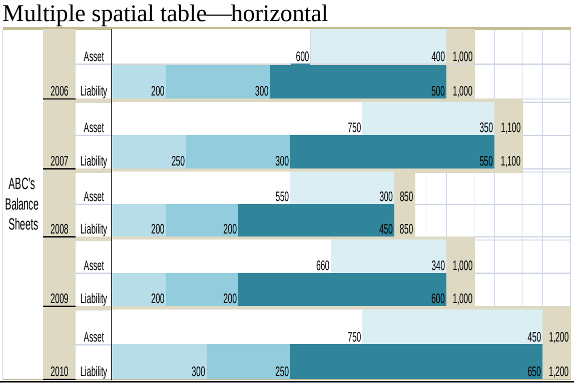
3 Multiple spatial table—vertical up



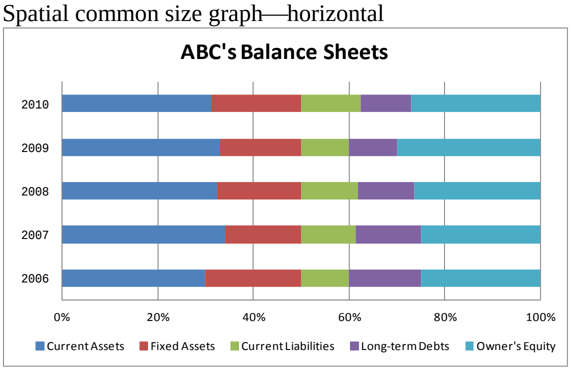
8 Spatial common size graph—vertical



4 Multiple spatial table—horizontal



9 Spatial common size graph—horizontal

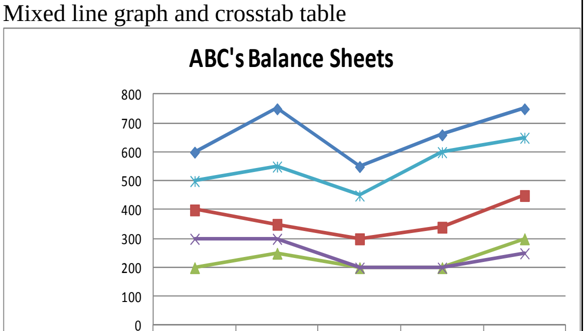


5 Mixed of symbolic table and graphlets

ABC's Balance Sheets

	2006	2007	2008	2009	2010	Trends
Current Assets						
Cash and cash equivalents	150,000	200,000	100,000	175,000	150,000	
Accounts receivables	300,000	300,000	250,000	210,000	350,000	
Inventory	150,000	250,000	200,000	275,000	250,000	
Fixed Assets						
Land	200,000	200,000	200,000	200,000	250,000	
Property and Plants (Net)	100,000	85,000	70,000	55,000	95,000	
Equipments (Net)	100,000	65,000	30,000	85,000	105,000	
Total Assets	1,000,000	1,100,000	850,000	1,000,000	1,200,000	
Current Liabilities						
Accounts payable	200,000	250,000	200,000	200,000	300,000	
Long-term Debts						
Long-term loans	300,000	300,000	200,000	200,000	250,000	
Owner's Equity						
Common shares	400,000	400,000	400,000	400,000	500,000	
Retain earnings	100,000	150,000	50,000	200,000	150,000	
Liabilities and Owner's Equity	1,000,000	1,100,000	850,000	1,000,000	1,200,000	

10 Mixed line graph and crosstab table



	2006	2007	2008	2009	2010
Current Assets	600,000	750,000	550,000	660,000	750,000
Fixed Assets	400000	350000	300000	340000	450000
Current Liabilities	200,000	250,000	200,000	200,000	300,000
Long-term Debts	300,000	300,000	200,000	200,000	250,000
Owner's Equity	500000	550000	450000	600000	650000

Figure 3. Alternative balance sheet visuals.

Perceived learning performance. The respondent was asked to tick as many types of learning performance as he/she perceived from viewing each individual balance sheet visual. Based on Bloom's typology, six levels of learning are included, consisting of Cph (comprehend), App (apply), Ana (analyze), Syn (synthesize), Eva (evaluate) and Ins (insight). This framework has been widely used in teaching and learning research with an implication that learning performance will be higher when the level increases.

Table 3

Matching Between Type of Task Activity and Visual Representation

Task activity	Visual representation		
	Symbolic	Spatial	Mixed
C (Confirmation) that the balance sheet discloses data according to accounting standards	X		
R (Review) that the financial position is accurate	X	X	
U (Understanding) the financial status and position			X
D (Decision) choices being formed from the assessment of the firm's financial position			X

Learning style. The respondent was asked to go to Felder's Website at the North Carolina State University Website (http://www2ncsu.edu/felder~public/ILSdir/ILAweb.html) and proceed through the assessment in order to obtain his/her four types of learning style scores and send them to the second author via the university LMS. This variable is included as the moderating variable between the cognitive fit and learning performance. Among the four dimensions of learning style, the visual-verbal dimension will be included in further analyses.

Results

With combined response rate of 54.9% (62 from a total of 104 subjects) and very similar profiles between the executive class and regular class, the analyses were then carried out by combining both student groups. First, descriptive statistics will be presented on the two main variables and one control variable as follows: visual-task-fitting preference, learning performance and learning style. Then non-parametric statistics will be used to test the relationships between constructs, since nominal and ordinal scales were used in the survey.

Visual-Task-Fitting Preference

This construct is measured by the extent of preference the subject has given to each visual and each task activity. In Table 4, alternative "spatial table" visuals (#1-4) received higher rating scores of preference than regular "graph" visuals (#6-8). However, the "mixed" of symbolic and spatial visuals (#5 and #10) received the highest mean scores (above 4.5 from a seven-point scale) across different types of task activities.

The pattern of average means appears progressive from basic task activity like "confirmation" to "review", then to "understanding" and finally to "decision-making". However, spatial tables of different configurations received a higher rating on "understanding" activity whereas simple bar graphs (#6 and #7) attained greater voting scores than common-size graphs for the two similar activities. No statistically significant difference was found among students with and without experience. Neither did gender nor learning style contribute to the difference in their combined scores of preference. However, different majors seemed to have different levels of acceptance. AIS, SIT and MIS majors had different mean rank on the preference scores of visuals used for decision-task activity: 21.6, 35.5 and 32.3, respectively. The Kruskal-Wallis Chi-square statistic yields a value of 7.238 (df = 2.62, p = 0.027).

Table 4
Means of the Level Preference on Individual Balance Sheet Visuals

	Balance sheet visuals	Task activity			
		Confirm	Review	Understand	Decide
1	Single spatial table	4.08	3.97	4.63	4.15
2	Multiple spatial table—vertical down	4.00	3.98	4.27	4.18
3	Multiple spatial table—vertical up	4.26	4.35	4.63	4.39
4	Multiple spatial table—horizontal	4.03	4.15	4.35	4.16
5	Mixed symbolic table—graphlets	4.66	4.84	4.84	4.60
6	Vertical graph	3.65	3.85	4.11	4.37
7	Horizontal graph	3.50	3.68	3.90	4.03
8	Common size graph—vertical	2.94	2.95	3.26	3.11
9	Common size graph—horizontal	2.89	2.98	3.37	3.32
10	Mixed line graph and crosstab table	4.45	4.52	4.66	4.82
	Means of average combined scores	3.84	3.93	4.20	4.11

Regardless of the type of activity, the respondents were asked about their preferred types of visual by comparing one type of graph with another. The preference percentages between the original tables ("symbolic") versus the "spatial table" are 56.5% and 43.5%, the "spatial table" versus the "mixed" of numbers and graphs are 35.3% and 64.5%, and the "mixed" versus the "graph" are 72.6% and 26.4%, respectively. The voting percentages appear to show that the "graph", the "spatial table", the "original or symbolic" and the "mixed" are the preferred visuals in ascending order.

Perceived Learning Performance

The multiple response method is used to analyze the learning performance construct. Despite of the implied hierarchical levels of Bloom's learning performances, the authors chose to treat these learning performance items without leveling. Table 5 shows the frequency (in percent) of responses and cases. Three out of four "spatial table" visuals are perceived to fit with the task activity of "comprehension". The balance sheet visuals included in this study seem to help with the analysis-task activity more than the other learning performance indicators. The higher learning performance levels such as "synthesis", "evaluation" and "insight" had not been chosen by a majority of respondents. One possible explanation is that students in the Masters Degree program tend to be trained to do analysis tasks consisting of more than synthesis and evaluation. Also, the survey instrument was developed without tying it to any specific business context. Thus, the respondents may not be able to perceive higher levels of learning performance, especially at the insight level.

Learning Style

How people see, think and learn may depend on their individual, innate learning styles. Some might prefer active as compared to reflective learning, sensing rather than intuitive, visual rather than verbal and sequential rather than global. Felder and Solomon's (1998) learning style model was employed for the study. As shown in Table 6, the two groups exhibit similar learning styles for the first three dimensions such that more of them prefer active learning, use sense-making and are visually oriented. In fact, the highest mean scores are visual orientation in both groups (6.4 and 6.3). Though the sequential learning style is found more in the executive class (53.6%), the global learning style is more common in the regular class. Students with less experience seemed to rate themselves as global-style learners (47.9%).

Table 5

Multiple Responses of Learning Performance

Balance sheet visuals	No.	Comprehend (%)	Application (%)	Analysis (%)	Synthesis (%)	Evaluation (%)	Insight (%)
1 Single spatial table	145	34.5	13.8	21.4	3.4	20.0	6.9
	62	80.6	32.3	50.0	8.1	46.8	16.1
2 Multiple spatial table—vertical down	157	26.1	15.9	24.8	5.1	24.2	3.8
	61	67.2	41.0	63.9	13.1	62.3	9.8
3 Multiple spatial table—vertical up	163	25.8	17.2	27.0	3.1	24.5	2.5
	62	67.7	45.2	71.0	8.1	64.5	6.5
4 Multiple spatial table - horizontal	162	24.7	18.5	21.6	7.4	24.1	3.7
	60	66.7	50.0	58.3	20.0	65.0	10.0
5 Mixed symbolic table—graphlets	176	23.9	15.3	24.4	9.1	22.2	5.1
	59	71.2	45.8	72.9	27.1	66.1	15.3
6 Vertical graph	167	22.2	16.2	25.1	10.2	21.6	4.8
	59	62.7	45.8	71.2	28.8	61.0	13.6
7 Horizontal graph	144	25.7	17.4	23.6	9.0	20.8	3.5
	57	64.9	43.9	59.6	22.8	52.6	8.8
8 Common size graph—vertical	96	24.0	19.8	24.0	9.4	20.8	2.1
	53	43.4	35.8	43.4	17.0	37.7	3.8
9 Common size graph - horizontal	103	25.2	16.5	26.2	8.7	21.4	1.9
	53	49.1	32.1	50.9	17.0	41.5	3.8
10 Mixed line graph and crosstab table	209	18.7	17.2	23.4	11.0	22.0	7.7
	57	68.4	63.2	86.0	40.4	80.7	28.1

Notes. The two rows for each visual show percentage of responses by respondents on the upper row and percentage of cases the respondents tick a particular learning performance. For example, balance sheet visual #10 or the "mixed line graph and crosstab table" visual, there are 209 ticks (responses) by 57 respondents, 23.4% of the responses and 86% of the cases indicated that visual#10 fits with their "analysis" learning performance.

Table 6

Respondent's Learning Styles

Learning style	Group 1: Executive ($N1$ = 56)			Group 2: Regular ($N2$ = 48)		
(N = 104)	(1)	(2)	Equal	(1)	(2)	Equal
(1) Active/(2) reflective	64.3%	26.8%	8.9%	66.7%	14.6%	18.8%
	4.2	3.0		3.0	3.3	
(1) Sensing/(2) intuitive	67.9%	19.6%	12.5%	54.2%	37.5%	8.3%
	5.0	4.3		3.5	3.2	
(1) Visual/(2) verbal	91.1%	8.9%	0%	85.4%	12.5%	2.1%
	6.4	3.4		6.3	2.7	
(1) Sequential/(2) global	53.6%	35.7%	10.7%	45.8%	47.9%	6.2%
	3.0	2.9		2.9	3.2	

Notes. The table reports percentage of respondents identifying their individual learning styles. For example, 91.1% of the executive class perceived themselves as being visual-oriented as compared to only 8.9% verbal-oriented. Only 54.9% of these respondents continue to respond to the visual-task-fitting preference and perceived learning performance survey.

Hypothesis Testing

Descriptive statistics and non-parametric statistics are used to provide preliminary evidence of the proposed relationships. For the first hypothesis that examines whether a user's mental model when performing a given task activity will fit with the type of visual presented, Kruskal Wallis One-way ANOVA (analysis of variance) was used. The ten balance sheet visuals were combined into three subgroups, namely, "spatial table", "graph" and "mixed". Table 7 shows the mean rank difference between groups, Chi-square statistics, and *p*-value of the visual-task-fitting preference measures. Very few differences of preferred visuals for different types of activity were found. The only type of visual that showed any group difference is "spatial table": between those with and without work experience (Chi-square = 3.893, $p = 0.048$), male and female (Chi-square = 7.705, $p = 0.006$) and AIS, MIS, SIT major (Chi-square = 9.038, $p = 0.01$). Respondents with different learning styles do not seem to exhibit any difference in their visual-task-fitting preferences. This finding indicates that Hypothesis 1 is not supported.

Table 7

Kruskal Wallis One-Way ANOVA for the Visual-Task-Fitting Preference

Differences between groups	Spatial table	Graph	Mixed visual
Work experience: with versus without	23.84, 34.16, 3.893*	25.94, 33.43, 2.055	37.56, 29.39, 2.449
Gender: male versus female	38.5, 25.74, 7.705**	31.18, 31.76, 0.016	31.00, 31.91, 0.039
Major: AIS, MIS, SIT	20.68, 36.23, 29.00, 9.038**	25.26, 33.13,41.25, 3.543	32.47, 31.43, 28.13, 0.191
Style: active, neutral, reflective	35.38, 36.31, 28.68, 2.148	27.83, 25.19, 33.06, 1.795	33.83, 37.00, 39.00, 1.749
Style: sensing, neutral, intuitive	27.30, 36.50, 32.29, 1.543	27.68, 29.30, 33.08, 1.246	34.15, 21.90, 30.51, 1.981
Style: visual, neutral, verbal	29.31, N/A, 31.25, 0.083	37.56, N/A, 30.01, 1.261	34.75, N/A, 30.43, 0.413
Style: sequential, neutral, global	32.38, 21.92, 31.69, 1.766	29.81, 29.58, 32.19, 0.286	33.54, 27.50, 29.71, 0.894

Notes. * $p < = 0.05$; ** $p < = 0.01$.

A similar analysis was carried out for perceived learning performance. However, due to low response rates to these questions, some of the Kruskal Wallis tests could not be performed and, for those performable tests, none is statistically significant, indicating no support for Hypothesis 2. That is, visual-task-fitting preference does not seem to contribute to the respondents' perceived learning performance.

Discussion and Conclusions

Current research issues in business visualization focus on the relationship between cognitive fit and decision-making performance. However, a priori to decision-making is the learning process that a user of business visuals has to have in order to understand and gain insight into the problem domain itself. Nevertheless, visuals are used to complement other information in a business report. Therefore, the study of what complementary visuals will fit with what tasks and, in turn, allow them to understand the information better can definitely add another perspective to the existing body of business visualization literature. Besides gaining insights into the information received, management may be able to devise more innovative ideas and greater numbers of alternative solutions (Stoyanov & Kirschner, 2007). Using perceived-learning performance instead of decision-making performance in the business context can further contribute to the existing body of knowledge.

Mixed results are found from the present exploratory study. No relationship was found between the type of activity and the type of visual. Neither was there any difference in the preferred visual type between people with or without experience, accounting or non-accounting majors, visual- or verbal- oriented individuals. It should be noted that this exploratory study found that the applicability of the cognitive fit theory on learning performance might not be as useful as in its original application toward decision-making performance (Vessey, 1991). As it stands, mixed symbolic tables with graphics are the most preferred visuals for analysis-task activity of a balance sheet. Unlike the decision-making process, the learning process may take on a different information-processing dimension. Determining the right information in the right format using appropriate visuals may not be a "cut and dried" decision environment. Thus, both symbolic and spatial data may actually be necessary to balance sheet users in today's complex information processing environment. Thus, standard setters may want to pay more attention to not only the disclosure of the right accounting numbers but also the right visual form of financial reports as well.

In recent years, many commercial software packages have extended a visualization capability to their applications. Many of these visuals were made available just for the sake of having them there. At times, they are "chartjunk" and might result in more harm than good for report users. Configuration costs increase in order to make these unnecessary visuals available to the users and should be reconsidered with the insights from the findings of the present exploratory research. In as much as they should be, the visuals from a financial statement have not been presented for external stakeholders. For internal report users, the question pertaining to which visuals should be used to present the financial statement such that they will fit the information processing tasks of these users might have been asked but has not been widely researched. One wonders if complex accounting data can be visualized better, could this make many past financial crises less severe, for example, the 1997 Asian crisis and the 2008 hamburger crisis.

References

Ackoff, R. L. (1967). Management misinformation systems. *Management Science, 14*(4), B147-B156.

Anderson, L. W., & Krathwohl, D. R. (2001). *A taxonomy for learning, teaching, and assessing: A revision of Bloom's taxonomy of educational objectives*. New York, USA: Addison-Wesley Longman.

Andrienko, N., & Andrienko, G. (2003). Informed spatial decisions through coordinated views. *Information Visualization, 2,* 270-285.

Benbasat, I., & Dexter, A. S. (1986). An investigation of the effectiveness of color and graphical information presentation under varying time constraints. *MIS Quarterly, 10*(1), 59-84.

Bloom, B. (1956). *Taxonomy of educational objectives handbook I: Cognitive domain*. New York: McGraw-Hill.

Borner, K., Chen, C., & Boyack, K. W. (2003). Visualizing knowledge domains. *Annual Review of Information Science and Technology, 37,* 1-58.

Buckhard, R. A. (2005). Towards a framework and a model for knowledge visualization: Synergies between information and knowledge visualization (Unpublished manuscript, University of St. Gallen).

Buckhard, R. A., & Stott, J. (2005). Knowledge visualization: A comparative study between project tube maps and gantt charts (Unpublished manuscript, University of St. Gallen).

Buttenfield, B. P., & Beard, M. K. (1994). *Graphical and geographical components of data quality*. In D. Unwin, & H. Hearnshaw, (Eds.), *Visualization in geographic information systems* (pp. 150-157). John Wiley & Sons: London.

Ceniceros, R. (1998, May). Risk mapping helps in visualizing exposures. *Business Insurance, 32*.

Cole, G. H. (2003). Illustrating the statement of cash flows. *National Public Accountant*, 14-15.

Cormier-Chisholm, J. (2002). Market fishing for four dimensions. *Futures*, 58-60.

D' Andrea, V. M. (2003). Organizing teaching and learning outcomes-based planning. In H. Fry, S. Ketteridge, & S. Marshall (Eds.), *A handbook for teaching and learning in higher education: Enhancing academic practice* (2nd ed., pp. 26-41). Routledge, a member of the Taylor & Francis Group, an Informa Business.

Dennis, A. R., & Carte, T. A. (1998). Using geographical information systems for decision making: Extending congitive fit theory to map-based presentations. *Information Systems Research, 9*(2), 194-203.

Dumas, J. S., & Redish, J. C. (1999). *A practical guide to usability testing*: *Intellect books.*

Eve, A. W. (1984). Graphics a potentially powerful force in business world affecting information assimilation, managerial style. *Computerworld, 18,* 60-61.

Fassin, Y. (2008). Imperfections and shortcomings of the stakeholder model's graphical representation. *Journal of Business Ethics, 80,* 879-888.

Felder, R. M., & Silverman, L. K. (1988). Learning and teaching styles in engineering education. *Journal of Engineering Education, 78*(7), 674-681.

Felder, R. M., & Solomon, B. A. (1998). *Index of learning styles.* Retrieved August 1, 2008, from www.ncsu.edu/felder-public/ILSpage.html

Few, S. (2004). *Show me the numbers: Designing tables and graphs to Enlighten*. Oakland, California: Analytics Press.

Gershon, N. (1994). From perception to visualization. In L. Rosenblum et al. (Ed.), *Scientific visualization: Advances and challenges.* Academic Press: San Diego, C. A..

Gonzales, M. L. (2004). More than pie charts. *Intelligent Enterprise, 7*(17), 12-14.

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

ICAEW. (2003). *New reporting models for business*. The Institute of Chartered Accountants in England and Wales.

Johnson-Laird, P. N. (1998). Imagery, visualization, and thinking. In J. Hochberg (Ed.), *Perception and cognition at the century's end* (pp. 441-467). San Diego, C. A.: Academic Press.

Kaplan, R. S., & Norton, D. P. (2001). *The strategy-focused organization*. Boston, M. A.: Harvard Business School Press.

Kim, K., Grimm, L. R., & Markman, A. B. (2007). Self-construal and the processing of covariation information in causal reasoning. *Memory and Cognition, 35*(6), 1337-1343.

Lee, J. M., & Maclachlan, J. (1986). The effects of 3D imagery on managerial data interpretation. *MIS Quarterly, 10*(3), 256-270.

Leibs, S. (2002, July). Now you see it. *CFO, 18,* 61-62, 64, 66.

Lengler, R., & Eppler, M. J. (2008). *A periodic table of visualization methods*©. Retrieved July 25, 2008, from http://www.visual-literacy.org/periodic_table/periodic_table.html

Lin, J., Keogh, E., & Lonardi, S. (2005). Visualizing and discovering non-trivial patterns in large time series databases. *Information Visualization, 4,* 61-82.

Moallem, M. (2007/2008). Accommodating individual differences in the design of online learning environments: A comparative study. *Journal of Research on Technology in Education, 40*(2), 217-245.

Potts, J. S. (1975). The place of computer graphics in the business community. *Data Management, 13*(9), 44.

Roa, K. V. (1985). Graphics in business information systems. *Journal of Systems Management, 36*(7), 18-21.

Rubin, J. (1994). *Handbook of usability testing: How to plan, design, and conduct effective tests.* New York: John Wiley.

Sachinopoulou, A. (2001). *Multidimensional visualization—VTT-TIED-research notes 2114.* VTT Electronics, Technical Research Centre of Finland.

Sadler-Trainor, G. (2005). A visual overdose? Visual communications in public relations. *Public Relations Quarterly, 50,* 7-9.

Sangole, A., & Knopf, G. K. (2002). Representing high-dimensional data sets as closed surfaces. *Information Visualization, 1,* 111-119.

Stoyanov, S., & Kirschner, P. (2007). Effect of problem solving support and cognitive styles on idea generation: Implications for technology-enhanced learning. *Journal of Research on Technology in Education, 40*(1), 49-63.

Taggart, W. J., & Tharp, M. O. (1977). A survey of information requirements analysis techniques. *ACM Computing Surveys (CSUR), 9*(4), 273-290.

Talbot, R. P. (1989). Valuing differences in thinking styles to improve individual and team performance. *National Productivity Review, 9*(1), 35-49.

Thomson, J., Hetzler, B., MacEachren, A., Gahegan, M., & Pavel, M. (2005). A typology for visualizing uncertainty. Paper presented at the *Conference on Visualization and Data Analysis (part of the IS&T/SPIE Symposium on Electronic Imaging)* San Jose, C. A., USA, 2005.

Ufelder, S. (2000). Envision this. *Computerworld, 34,* 94-95.

Venkata, R. K. (1985). Graphics in business information systems. *Journal of Systems Management, 36*(7), 18-21.

Vessey, I. (1991). Cognitive fit: A theory-based analysis of the graphs versus tables literature. *Decision Sciences, 22*(2), 219-240.

Vessey, I. (1994). The effect of information presentation on decision making: A cost-benefit analysis. *Information and Management, 27,* 103-117.

Ward, M. O. (2002). A taxonomy of glyph placement strategies for multidimensional data visualization. *Information Visualization, 1*(194-210).

Zimowski, M. F., & Wothke, W. (1986). *The measurement of human variation in spatial visualizing ability: A process-oriented perspective (Report #143)*: Human Engineering Lab at the Johnson O'Connor Research Foundation, Chicago, Illinois, USA.