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Studies on Visual Analytics in the Information Systems Literature: A Review

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Research-in-Progress

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Abstract

We present a review on the status-quo of visual analytics research in the information systems (IS) literature with a focus on how visual analytics has been used to improve decision-making. We show that although progress has been made, the IS literature is still in its early stage of visual analytics research, with many important questions unanswered. Three broad categories of questions deserve further investigation: how does visual analytics affect the human decision process, how does it affect decision outcomes such as accuracy, confidence, and satisfaction, and how to design a visual analytical system to achieve these goals?

Key words

Visual analytics, visualization, data representation, interactivity, decision-making

Introduction

Visual analytics is the science of analytical reasoning facilitated by interactive visual interfaces (Thomas and Cook 2005, p.4). It aids the understanding of data by leveraging the human visual system's highly tuned ability to see patterns, spot trends, and identify outliers (Heer et al. 2010). It provides important values to complex problem-solving and decision-making (Cybulski et al. 2015) and has been widely applied in areas such as law enforcement, critical infrastructure protection, financial fraud detection, real-time situation assessment, and scientific inquiry (Kielman et al. 2009). In business, managers use visual analytics for visual decision making (Williams et al. 2015).

Ever since the seminal work by Thomas and Cook (2005), a large number of studies have been conducted to examine visual analytics. A quick search for the subject term "visual analytics" on *EBSCO Academic Search Complete* (www.ebsco.com) at the end of September 2018 returned 1,033 papers published in peer-reviewed academic journals; most of the papers, though, appeared in computer science and engineering (CS&E) literature such as *Computer Graphics Forum* (142 papers), *IEEE Computer Graphics & Applications* (120 papers), and *Journal of Visual Languages & Computing* (32 papers). The Information Systems (IS) literature, in contrast, published less number of papers on this topic.

Since the IS discipline is still in its early stage of conducting visual analytics research, in this paper, we conduct a review of the status-quo of research in the IS literature, with the goals of understanding what progress has been made and what future research directions may exist. In the following sections, we first provide a brief introduction of visual analytics, then elaborate the method for the review. Preliminary findings are then discussed, followed by discussions on future research directions.

Visual Analytics: A Brief Introduction

Visual analytics, as mentioned above, is the science of analytical reasoning facilitated by interactive visual interfaces. It is used to synthesize information and derive insight from massive, dynamic, ambiguous, and sometimes conflicting data. It also detects the expected and discovers the unexpected, provides timely, defensible, and understandable assessments, and communicates assessment effectively for action (Thomas and Cook 2005). Visual analytics performs some major tasks such as exploration, dashboards, reporting, and alerting (Zhang et al. 2012). These tasks determine the wide adoption of visual analytics in many fields (Kielman et al. 2009).

Visual analytics is an outgrowth of the fields of scientific and information visualization, but includes technologies from many other fields such as knowledge management, statistical analysis, cognitive science, and decision science (Wong and Thomas 2004). Thus, the boundary between visual analytics and other areas of information visualizations is not quite clear. Nevertheless, a couple of fundamental techniques, including visual representation and interactivity (Thomas and Cook 2006), distinguish it from other analytical and visualization techniques. First is visual representation, or data visualization, that uses graphic formats to represent data for knowledge discovery. To date, a large number of visualization techniques have been developed to represent numerical data (e.g., histogram, scatterplot, heatmap, and parallel coordinates), geographic data (e.g., map), and network data (e.g., tree map)(Zhang et al. 2012). New types of visualization tools, such as quantile-quantile plot, scatter plot matrix, graduated symbol maps, and arc diagram are also introduced (Heer et al. 2010). The ability to represent multifaceted data makes data visualization a popular medium for journalistic storytelling, and professionals have been using visual analytics in news stories to discuss complex issues such as elections, economy, and global health (Santos et al. 2017).

The second fundamental technique of visual analytics is interactivity with visualized data (Parsons and Sedig 2014; Pike et al. 2009). Such interactivity allows users to further explore data to generate understanding and insights (Remco et al. 2009; Saggi and Jain 2018). Regarding this technique, Yi et al (2007) provide a popular taxonomy of seven general categories of interactive features including selection, exploration, reconfiguration, encoding, abstraction/elaboration, filtering, and connection. This taxonomy is widely adopted in the literature (Dilla et al. 2010; Dilla and Raschke 2015; Pike et al. 2009) and inspires other classifications of interaction effects (Heer and Shneiderman 2012). In addition, several properties of interactivity have been studied, such as appearance, complexity, configuration, density, and dynamism (Parsons and Sedig 2014). These properties determine the extent of interactivity with visualized data.

Although visual analytics has overlapping with other means of conveying information such as data representation (using static graphs such as bar/column/pie chart) and animation (using animated graphs)(Tversky et al. 2002), the distinctions are noteworthy. On one hand, the static graphs lack the ability to interact with data and render changes over time, making it inferior to interactive data visualization to recognize patterns, relationships, and so on. On the other hand, animation may hinder learning due to lack of control: the animation may be too complex or too fast to be accurately perceived by the user, demanding "judicious use of interactivity" to overcome these disadvantages (Tversky et al. 2002). Thus, strictly speaking, neither static graphs nor animation fall into the domain of visual analytics, although the elements of both can be used to enhance visual analytics.

Visual analytics has become a multidisciplinary field that includes several focused research areas, such as: analytical reasoning that enables users to obtain deep insights to directly support assessment, planning, and decision making; visual representations and interaction that allow users to see, explore, and understand large amounts of information at once; data representation and transformation that convert all types of conflicting and dynamic data in ways that support visualization and analysis; and production, presentation, and dissemination of the results to communicate information to the audiences (Thomas and Cook 2005). The development of visual analytics has been phenomenal in the last decade.

A few review studies have been conducted to examine the applications of visual analytics in different fields. Dilla et al (2010), for example, provide a review on interactive data visualization in accounting information systems, suggesting that both task characteristics and decision maker characteristics influence interactive data visualization techniques, and those techniques influence decision processes and outcomes (e.g., information acquisition, search strategy, time, and accuracy). They reveal a considerable gap between the use of interactive visualization techniques for accounting data and the research examining the effects of these techniques on decision making, calling for more studies on those effects.

Healy and Moody (2014) then provide a review on data visualization in sociology. They show that many visual effects can be used to represent research data such as tilted heat map, parallel coordinates plot, and vector diagram. Nevertheless, they argue that premier journals in sociology publish articles with many tables but few figures, which is opposite to natural science journals. Thus, they conclude that despite a promising early beginning, sociology has lagged in the use of visual tools.

Finally, with a focus on design issues, Adagha et al. (2017) did a review on 470 visual analytics papers published between 2006 and 2012. They made six inductively derived design recommendations, such as facilitating the continuous acquisition of situation awareness, incorporating attributes that support seamless collaboration between users, and designing the interface that acts as a vehicle of creativity and self-expression for the decision maker.

These reviews show the great potential – and in some cases wide adoption – of visual analytics in research and practice. Yet, its adoption has been uneven across disciplines. We study its status-quo in the IS literature.

Research Method

Following established methods of systematic review (Adagha et al. 2017; Higgins and Green 2008; Schwarz et al. 2007), we conduct the research in six stages: identifying the search criteria, searching for relevant papers, developing a coding scheme, coding and data extraction, analysis of data, and synthesis of findings.

For the search criteria, we examine peer-reviewed IS papers published since 2005 when the seminal work of Thomas and Cook (2005) was published. This is a common milestone in similar review studies (Adagha et al. 2017). Both journal and conference papers are examined. For journal papers, we searched based on the ABDC (Australian Business Deans Council; www.abdc.edu.au) Journal Quality List, which is a popular guide of high quality research journals in the IS field. We restricted search on journals ranked at level B or higher. For conference papers, we searched in proceedings from five leading IS conferences including ICIS, AMCIS, EJIS, HICSS, and PACIS. “Visual analytics” is the only subject word used for the search.

Using the above criteria, we searched databases such as EBSCO, ScienceDirect, AIS e-Library, and the websites of the journals whenever needed. Each paper was examined carefully to make sure it addresses visual analytics. For example, studies on traditional, static information representation are excluded. The search yielded a list of 56 journal papers and 24 conference papers, shown in Table 1 and Table 2.

We further developed a coding scheme for data extraction. We code the authors, publication year, journal name, research context, visual analytics features, impact on decision process, and impact on decision outcomes from each paper. These variables enable us to synthesize studies, come up with a summary of major findings, and more importantly, recognize gaps.

Data extraction and analysis is a time-consuming process. At the time this research-in-progress was prepared, the process has not been finished. Only preliminary findings were reported in the next section.

Journal	Paper Count
AIS Transactions on Human-Computer Interaction	2
Australasian Journal of Information Systems	1
Behavior and Information Technology	1
Business & Information Systems Engineering	2
Communications of the ACM	4
Communications of the Association for Information Systems	1
Computer Supported Cooperative Work	1
Computers in Human Behavior	2
Decision Support Systems	5
Expert Systems with Applications	8
Government Information Quarterly	4
Information Processing and Management	4
Information Systems Frontiers	3
Information Technology and People	1
International Journal of Information Management	5

Journal of Computer Information Systems	1
Journal of Management Information Systems	3
Journal of the American Society for Information Science and Technology (JASIST)/Journal of the Association for Information Science and Technology (JAIST)	4
Journal of the Association for Information Systems	1
MIS Quarterly Executive	1
Requirements Engineering	2
Total	56

Note: Journals without any qualified papers found were not shown in the table.

Table 1. Journal papers.

Conference	Count
AMCIS (Americas Conference on Information Systems)	3
ECIS (European Conference on Information Systems)	3
HICSS (Hawaii International Conference on System Sciences)	16
ICIS (International Conference on Information Systems)	2
PACIS (Pacific-Asia Conference on Information Systems)	0
Total	24

Table 2. Conference papers.

Preliminary Findings

In this section, we report some preliminary findings from the literature review. We first provide descriptive information of the articles, then give examples of the contexts and visual effects examined in those articles. Next, we discuss findings related to the impact of visual analytics on decision process and decision outcomes. Finally, we explore challenges facing visual analytics research in the IS literature.

Descriptive information

Our preliminary findings show that IS is behind other fields, especially CS&E, in studying visual analytics. This makes sense because as an applied discipline, IS draws upon other fields such as CS&E and cognitive science (Fisher et al. 2011) for technological and cognitive foundations of research. Nevertheless, some progress has been made: as Figure 1 shows, more and more research on visual analytics has been published in recent years. Especially in the last two years, a large amount of studies have been published in conference proceedings, primarily due to two mini-tracks on visual analytics at HICSS (Ebert et al. 2017; Ebert et al. 2018).

To date, a large number of visual effects have been examined in the literature, ranging from basic charts such as x-y plot (Pohl et al. 2018), box plot (Angelini et al. 2018), and bar chart (Hsiao and Lin 2017) to relatively new types of charts such as heat map (Gregg 2010; Köpp et al. 2014), word cloud (Avvenuti et al. 2018), and tree map (Chen et al. 2013; Park et al. 2016). Some studies employed a combination of visual effects to render different types of information (Heer et al. 2010; Schardong et al. 2018; Scharl et al. 2016). These studies imply that using different data visualization effects is helpful to discover knowledge from multifaceted data and render different aspects of information to the audiences.

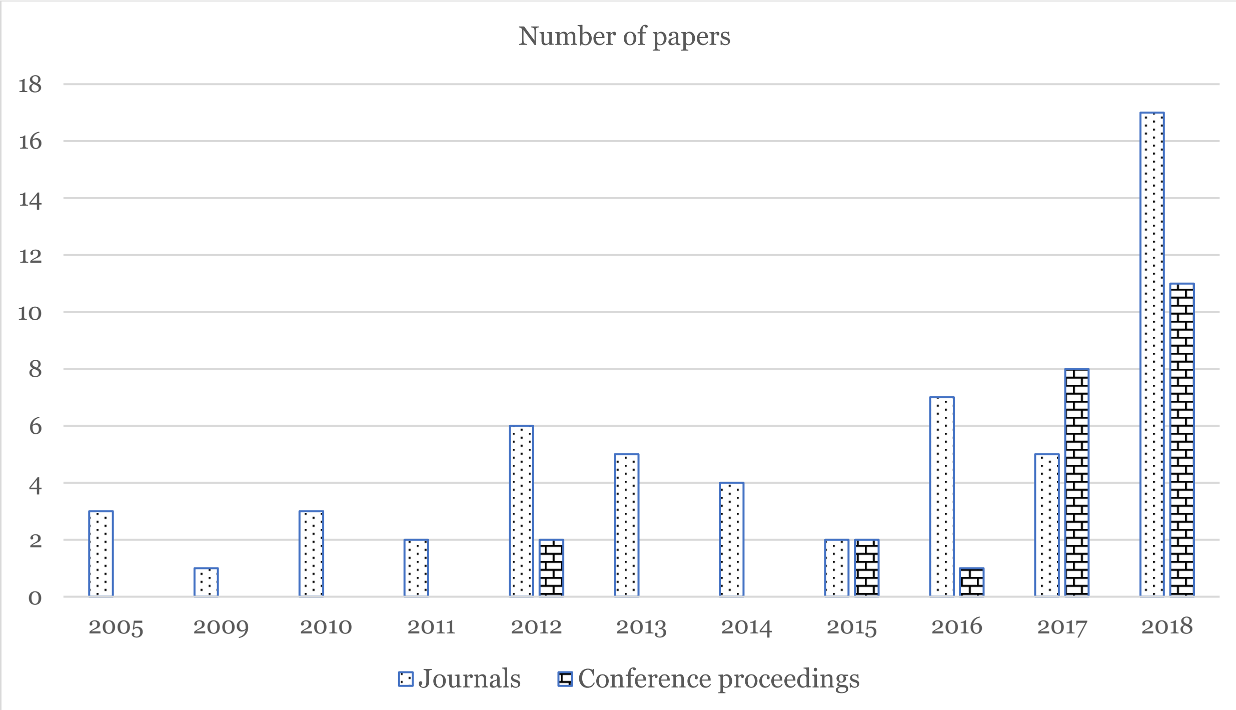

Figure 1. Publication of visual analytics papers over years

Research contexts and visual effects

A variety of research contexts have been employed to study visual analytics, and a spectrum of visual effects have been examined accordingly. Table 3 provides some examples. It suggests that visual analytics can be applied to any problem context so long as data are involved, and both basic (such as line chart) and advanced (such as heat map) visualizations can be used to represent data and enable analysis. A few studies have empirically tested the impact of these visual analytics features on decision performance, but most have remained in the developmental stage and await empirical tests.

Research context	Visual effects	Example findings
Disaster management (Ragini et al. 2018)	A variety of effects such as box plot and word cloud	A big data driven approach for disaster response through sentiment analysis with the support of visual analytics features.
Fraud (or other anomaly) detection such as unfair ratings (Sänger and Pernul 2018), tax evasion (Didimo et al. 2018), and network attacks (Erbacher and Forcht 2010)	parallel coordinates; network chart; radar chart	An interactive reputation system based on parallel coordinates was proposed and was found to increase users' ability in detecting malicious sellers (Sänger and Pernul 2018).
Project management (Zheng and Vaishnavi 2011)	Multi-dimensional perceptual maps	A visual exploration approach based on multi-dimensional perceptual maps was developed to assist in project prioritization and selection.

Salesforce analysis (Varshney et al. 2012)	A variation of the stem-leaf plot	A salesforce analytics application with an interactive visual interface was developed to allow users to explore the data and analytics at their own pace.
Social media analytics (SMA) (Chang et al. 2017; Santos et al. 2017; Soto et al. 2018)	A variety of charts such as map, heat map, and line chart (Chang et al. 2017).	Visual analytics based on social media data reveal differences in hotel guess reviews (Chang et al. 2017).
Supply chain management (Park et al. 2016)	A combination of chord diagram, tree map, matrix layout, and network chart	An interactive web-based visual analytic system was developed to support supply chain management.
Systems maintenance and latency diagnosis (Gregg 2010)	Heat map	Visual heat map provides insight into how a system performs and what kinds of latency end-user applications experience.

Table 3. Example studies on visual analytics

Impacts on decision process

The problem-solving and decision-making process influences how knowledge is discovered. A few studies examined the impact of visual analytics on decision process. For example:

- Improved process efficiency: Perdana et al. (2018) report that non-professional investors using an interactive data visualization tool for investment decisions reported improved heuristic information processing (in terms of efficiency in the process and efforts in making decisions) as compared to those without the interactive tool. This supports the view that visualized data can provide more information to decision-makers than plain data.
- Learning: Visual analytics was also found to enable better learning and understanding of complex issues such as healthcare (Wang and Santhanam 2015). A possible reason is that visualization enhances engagement of the users, which then drives learning outcomes such as understanding, long-term memory, and intention to change behaviors (Wang and Santhanam 2015).

In general, studies on the impact of visual analytics on decision process have been scarce. Most research focuses on developing new visual analytical tools to deal with specific decision problems (as Table 3 shows), but little has addressed empirically the impact on decision process. Experimental research should be conducted to examine how individuals' problem-solving, decision-making, and learning may change due to the use of visual analytics.

Impacts on decision outcomes

The goal of visual analytics is ultimately to improve decision outcomes. Regarding this, impacts of visual analytics on decision performance have been examined. For example:

- Transparency: Visualization may increase transparency in text analytics (Zablith et al 2017) and in detecting unfair ratings.
- Accuracy: A few studies on the impact of visual analytics on decision accuracy were conducted. For example, Sänger and Pernul (2018) find that an interactive reputation system using parallel coordinates helps to increase users' accuracy to detect malicious online sellers, and Perdana et al (2018) find that interactive data visualization tools enhance non-professional investors' accuracy in making investment decisions.
- Confidence: Increased confidence (or less uncertainty) in judgment was also observed. Perdana et al (2018) find that non-professional investors using interactive data visualization tools reported less perceived uncertainty, along with other benefits such as less time to make the decisions and improved accuracy.
- Insight: Gaining insight (Remco et al. 2009) – also called visual intelligence (Bačić and Fadlalla 2016) – is another benefit of visual analytics. Insight into system latency was gained via such tools (Gregg 2010).

Overall, empirical studies on the impact of visual analytics on decision outcomes are scarce, compared to studies that develop new analytical tools (see Table 3). This may be the case in early stage of technology development, but with the diffusion of visual analytics, more efforts are needed to empirically test its impact on decision performance.

Challenges in visual analytics

A challenge facing visual analytics is its adoption. In the midst of a rapidly changing information environment, visual analytic strategies are still not widely adopted, as managers tend to stick to their current work habits (Aigner 2013; Williams et al. 2015). In a study on journalists' and media professionals' opinions about interactive visualization of political data, Santos et al (2017) find that visualization and data analysis tools are still not easily accessible by those professionals, and are therefore less influential than they could be.

A possible reason for the limited adoption of visual analytics by decision makers such as managers is the challenge of preparing data for self-reliant visualization without the help of others (Lennerholt et al. 2018). In addition, some visual analytical systems may be too complex for users, so that system usability should be investigated and enhanced (Gorko et al. 2018). More importantly, "visual analytics must help the analyst discover unexpected and missing relationships that might lead to important insights (Thomas and Cook 2006)." This suggests that simply visualizing information is not attractive. Thus, there is a long way to go before visual analytics can be widely adopted to fulfill its promise. In addition to training users, more convenient and user-friendly tools may be designed and developed to assist users who do not possess advanced technical skills in dealing with interactive visualization.

Discussion and Concluding Remarks

Based on the preliminary findings, we acknowledge that progress has been made in studying visual analytics in the IS literature, but some fundamental issues remain unanswered and deserve further attention. First, how does interactive visualization tools affect the problem-solving and decision-making process of humans (Dilla et al. 2010; Williams et al. 2015), and how do they improve creativity (Cybulski et al. 2015)? Some changes in decision process are examined in terms of engagement (Wang and Santhanam 2015) and ease to understand data (Santos et al. 2017). Also, decision makers are expected to shift away from a problem-solving posture and embrace an inquisitive and constantly vigilant problem-finding style (Williams et al. 2015). But still, the process of stimulating and enabling human reasoning with the aid of interactive visualization tools is a highly unexplored field (Meyer et al. 2010).

Second, how does visualization and interactivity affect decision outcomes such as effort, accuracy, time, and even confidence? Judgmental confidence has been barely examined in the literature, despite the notion of overconfidence and mis-calibration of decision-makers in decision literature (Alba and Hutchinson 2000). An empirical study shows that when interactivity and visualization are offered separately, decision-makers become overconfident with their judgments, but when both features are offered together, decision-makers are less overconfident and more calibrated (Tang et al. 2014). A few studies have examined interactivity in data visualization (Varshney et al. 2012), but how interactivity influences decision outcomes have been barely tested. Several propositions regarding the impacts of task characteristics, individual characteristics, and visualization characteristics on decision outcomes (including efficiency and accuracy) are developed, but no empirical evidence has been offered (Dilla and Raschke 2015). With new visualization effects being developed to enhance data representation, it is a question of whether additional information indeed helps users make better decisions (Köpp et al. 2014). These outcome variables should be systematically analyzed.

The last issue deals with the design of visual analytics (Adagha et al. 2017). As mentioned above, a user-friendly design of visual analytical tools is a primary impediment to the adoption of the tools. In a conceptual paper, Baker et al (2009) proposed seven guidelines to design visual representations to enhance viewers' sensemaking, such as association, differentiation, ordering, quantitative variation, and so on. But these approaches await empirical test on their effectiveness. Besides, the current design of visual analytical tools focus on descriptive and predictive analytics (Lu et al. 2017; Park et al. 2016), but prescriptive analytics was seldom mentioned. This may be explored in future research as well.

Some research directions are summarized based on the above analysis and presented in Table 4. Future empirical studies may be conducted to address these issues.

Suggested Research Directions
How does visual analytics affect the problem-solving and decision-making process of individuals?
How does visual analytics improve creativity?
How does visual analytics influence decision outcomes such as accuracy, time, confidence, and user satisfaction?
What features of visual analytics can be improved for enhanced decision outcomes?
What features of visual analytics can be improved to address judgmental bias such as overconfidence?
The “dark” side of technology: How may visual analytics be used for political or other ulterior motives to mislead the target audience, and how can we detect this?

Table 4. Future research directions.

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