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DATA VISUALIZATION IN SUPPORT OF EXECUTIVE DECISION MAKING

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ABSTRACT

Aim/Purpose	This journal paper seeks to understand historical aspects of data management, leading to the current data issues faced by organizational executives in relation to big data and how best to present the information to circumvent big data challenges for executive strategic decision making.
Background	This journal paper seeks to understand what executives value in data visualization, based on the literature published from prior data studies.
Methodology	The qualitative methodology was used to understand the sentiments of executives and data analysts using semi-structured interview techniques.
Contribution	The preliminary findings can provide practical knowledge for data visualization designers, but can also provide academics with knowledge to reflect on and use, specifically in relation to information systems (IS) that integrate human experience with technology in more valuable and productive ways.
Findings	Preliminary results from interviews with executives and data analysts point to the relevance of understanding and effectively presenting the data source and the data journey, using the right data visualization technology to fit the nature of the data, creating an intuitive platform which enables collaboration and newness, the data presenter's ability to convey the data message and the alignment of the visualization to core the objectives as key criteria to be applied for successful data visualizations
Recommendations for Practitioners	Practitioners, specifically data analysts, should consider the results highlighted in the findings and adopt such recommendations when presenting data visualizations. These include data and premise understanding, ensuring alignment to the executive's objective, possessing the ability to convey messages succinctly and clearly to the audience, having knowledge of the domain to answer questions effectively, and using the right technology to convey the message.
Recommendation for Researchers	The importance of human cognitive and sensory processes and its impact in IS development is paramount. More focus can be placed on the psychological factors of technology acceptance. The current TAM model, used to describe use, identifies perceived usefulness and perceived ease-of-use as the primary consid-

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erations in technology adoption. However, factors that have been identified that impact on use do not express the importance of cognitive processes in technology adoption.

Future Research — Future research requires further focus on intangible and psychological factors that could affect technology adoption and use, as well as understanding data visualization effectiveness in corporate environments, not only predominantly within the Health sector. Lessons from Health sector studies in data visualization should be used as a platform.

Keywords — big data, data analytics, data visualization, cognitive fit theory, Cynefin Framework, executive strategic decision making

INTRODUCTION

> *"Executives are not paid for doing things they like to do. They are paid for getting the right things done – most of all in their specific task, the making of effective decisions"* (Drucker, 1966, p.167).

Over time, and as information technology has evolved, increasing volumes of data have been generated from varying sources, creating a data explosion (McAfee, Brynjolfsson, Davenport, Patil, & Barton, 2012) which, up until today, has resulted in increased organizational anxiety on how to effectively manage it for beneficial use, such as in formulating and implementing strategic decisions.

Today's organizational executives cannot operate reactively, but are required to make rigorous decisions and do not only have to understand the organization's internal strengths and weaknesses, but must also anticipate the effect of future external social, legal, political, and economic shifts in business practices to achieve organizational sustainability, competitive advantage and strategic growth (Donovan, Güss, & Naslund, 2015; Marques & Dhiman, 2016).

This exponential increase in data volume and complexity, known as big data, is posing new organizational challenges, as traditional data management philosophies and infrastructure can no longer account for or store, process. and support big data needs (Marz & Warren, 2015). Whilst living in a fast-paced world, how can organizational executives derive meaning from big data to make effective strategic decisions that can ultimately achieve the organization's vision?

This paper also identified literature that supports the use of data visualization, a big data analysis technique, to optimize the ability of organizational executives to effectively digest and use big data for strategic decision-making purposes and to summarize initial responses from executives of data visualization requirements. In order to achieve this objective, and to formulate qualitative questions that aim to prove or disprove the use of data visualization to optimize executive strategic decision-making, three dominant questions will be asked. These questions were defined based on an initial assessment of literature. Although literature did provide the benefits of data visualization in general, it did not assist in determining the key criterion for success in strategic decision making. Thus, the following questions were asked:

> *Research Question 1 (RQ1): What do individual organizational executives value and use in data for strategic decision-making purposes?*
>
> *Research Question 2 (RQ2): How does data visualization impact on an executive's ability to use and digest relevant information, including on their decision-making speed and confidence?*
>
> *Research Question 3 (RQ3): Should data analysts include or consider intangible elements into data visualization design?*

Literature was used from 2005 onwards due to the newness of the research topic, following the data evolution until its current position.

The remaining sections of this paper documents a brief literature collection process, the literature collected in relation to the three questions posed in the introduction, and, finally, provides a conclusion to the review.

LITERATURE ANALYSIS

In order to collect literature, a systematic literature review was performed as per the approach adopted by Gomez, Baron, and Fiore-Silfvast (2012). Key words including traditional data management, big data, data governance, strategic decision-making, data visualization, and cognition were searched within Information Systems, Business Management and Psychology library databases including ACM Digital Library, IEEE Explore, Springer Link, ScienceDirect, Academic Search Premier and PsychTESTS. Research papers were peer reviewed and only journal articles, books and conference proceedings were used. Traditional data literature was obtained post 2005, while big data and data visualization literature were obtained post 2010, with focus placed on literature published in 2015 and 2016 to highlight the most recent views of data visualization (Okoli & Schabram, 2010). Thereafter, literature obtained was developed into themes, enabling a logical and hierarchical flow of the literature (Gomez et al., 2012).The predominant approach and instrument used for data collection was semi-structured interviews (Brikci & Green, 2007). The population of interviewees comprised of executives tasked with strategic decision-making, as well as data analysts who are either internal (permanent employees) or external (consultants) of the organization. Executives and data analysts were purposefully selected from various industries including Financial, Technological, Banking, Education, Consulting, and IT Software. Executives levels included Chief Executive Officers (CEO's), Chief Financial Officers (CFO's), Chief Operational Officers (COO's), and General Managers. Purposeful sampling is aimed at those who are knowledgeable and experienced with the research topic, had good communication skills, and were available and willing to participate in the research study (Palinkas et al., 2015).Once the data was collected, thematic analysis identifying commonalities and differences within the data, was performed (Braun & Clarke, 2006). Further relationship analysis was performed to determine why certain explanations were evident, and a coding scheme was applied to determine if the problem statements had been addressed (Brikci & Green, 2007).

Data has been generated in various forms and used for a variety of purposes over many centuries. Data has no meaning when contained in isolation, while information provides meaning to the decision-maker by correlating and integrating data within a context (Świgoń, 2011). Knowledge is generated thereafter by grouping information together, which can add value to the decision-maker such as solving a problem (Mandinach, Honey, & Light, 2006). Today, data has become notably embedded in our daily lives, propelled by technological advances such as social media platforms. In the enterprise domain, data has traditionally been synonymous with structured data, capable of being distinctly and clearly identified, categorized, stored, and queried (Kaur & Monga, 2015). Its nature and type were homogenous, such as text, and was derived from limited sources, such as relational databases (Siddiqa et al., 2016). Due to the evolution of IT, which created platforms that communicate data in new and challenging ways, big data has become the new term, or phenomenon, which describes the nature of data in current times (De Mauro, Greco, & Grimaldi, 2015). Big data is classified into structured, semi-structured, unstructured, and streaming data, and if used collectively is termed as multi-structured data (Russom, 2013). Unstructured data is irregular in nature and cannot be grouped or arranged in a methodical manner, such as photographs and videos (Kaur & Monga, 2015).

Having understood traditional data and big data, what are the issues of big data that impact decision-making? Tables 1 and 2 provide a brief breakdown of the challenges from a general and data life cycle perspective.

Table 1. General big data challenges.

General Challenges	Solution	Reference
Processing power: data volume is superseding computational processing power resulting in Moore's Law becoming obsolete.	New technology is required to balance processing ability without negatively impacting on performance.	(Ammu & Irfanuddin, 2013)
Data volume	Cloud computing	(Armbrust et al., 2010)
Timely analytical capabilities of stored data.	Index structures must be agreed upon and created ahead to identify new criteria types more quickly.	(Ammu & Irfanuddin, 2013)
Supplementary information (meta-data) supporting data presentation.	Index structures must be agreed upon and created ahead to identify new criteria types more quickly.	(Ammu & Irfanuddin, 2013; Nasser & Tariq, 2015)
Data Quality	Implement big data governance policies to include standards for data accuracy, timeliness, completeness, credibility, data quality establishment, communication and evaluation.	(Jagadish et al., 2014; Khatri & Brown, 2010)
Regulatory requirements	Infuse big data governance policies with regulatory requirements in relation to customers, suppliers, employees and business stakeholders for all regions/locations where interaction is performed.	(Nasser & Tariq, 2015; Tallon, 2013)
Data security and access	Deploy risk and control strategies to secure data and queries such as encryption techniques, implement security technology related to big data and implement security and privacy of correlative big data. Include such procedures within the data governance policy.	(Ou, Qin, Yin, & Li, 2016)

Table 2. Big data life-cycle challenges.

Data Life-cycle Challenges	Solution	Reference
Data acquisition and recording: filtering, metadata generation and trustworthiness.	Identify filters that must be applied to data when acquired from data sources to reduce the amount of irrelevant data stored. Identify metadata to be used in analytical scenarios.	(Jagadish et al., 2014; Nasser & Tariq, 2015)
Data extraction and cleaning: effectively utilising unstructured and streaming data for analytics, error handling.	Automation of the data rules and metadata.	(Nasser & Tariq, 2015)
Data integration and aggregation: data heterogeneity and automating of integration and aggregation.	No definitive solution, but there is a need to move from unstructured to structured data for analysis.	(Jagadish et al., 2014; Nasser & Tariq, 2015)
Interpretation: wrong modelling, erroneous data, audience freedom to change presentations based on new assumptions.	Rich interactive visualisations which promote drill-down capabilities, providing information about the presentation itself, allowing errors to be detected and models to be queried.	(Nasser & Tariq, 2015)

Although significant strides have been made to explain and explore big data management, existing data management frameworks do not encompass or incorporate all objective and subjective data needs from data retrieval to retirement, including all governance requirements (Merino, Caballero, Rivas, Serrano, & Piattini, 2016; Priebe & Markus, 2015; Rajagopalan & Vellaipandiyan, 2013).

Regarding decision-making within organizations, data driven decision-making (D3M) was identified as a value-adding praxis (Cao, 2010). D3M uses data through enhanced analytics and related information management structures to provide evidence-based information for end-user decision-making (Duggan, 2014). Therefore, the process of decision-making is performed based on data analysis (Provost & Fawcett, 2013). However, a potential limitation of the data driven decision-making approach is that decision-makers can become too metric driven and may not open themselves up to thinking that drives innovation (Duncan & Buytendijk, 2015; Tickle, Speekenbrink, Tsetsos, Michael, & Summerfield, 2016). This sentiment is shared by Bouyssou, Dubois, Prade, and Pirlot, (2013) who highlight the importance of not only using data to enable investigation, but also stress that one must apply sensory and cognitive processes to aid effective decision-making. Regardless, based on a survey of 179 publicly trading firms by Massachusetts Institute of Technology (MIT) and Penn's Wharton School, D3M correlates to improved productivity, higher return on assets, asset utilisation, equity, and market value (Brynjolfsson, Hitt, & Kim, 2011; Provost & Fawcett, 2013).

Figure 1 explains a data driven decision-making framework using data as the core element within a hierarchical structure, much like the organizational structure, identifying cognitive processes that impact on the decision-making process (Mandinach & Jackson, 2012). The framework defines data as a raw constituent which has no meaning when contained in isolation (Cios, Pedrycz, & Swiniarski, 2012; Travica, 2014). Information provides meaning to the decision-maker by correlating data within a context, and knowledge is a grouping of information that has value or provides benefit to the decision-maker, such as solving a problem (Larose, 2014). The framework provides six cognitive processes that enable the decision-maker to reach the decision once knowledge is acquired (Mandinach & Jackson, 2012). Firstly, data must be collected (Sapsford & Jupp, 2006). The collection process is at the discretion of the decision-maker who decides what data and from which sources are relevant (McAfee et al., 2012). This first step is often driven by the decision-maker's question(s) that require answering and what is available. Not all data is available and therefore the decision-maker must consider the necessity of the data to the task at hand. The data must then be organized or categorized in some manner in order to initiate sense-making. By performing this process, data is translated into information, of which meaning can be derived (Chowdhury, 2010). Thereafter, the decision-maker can begin analytical processes, testing the correctness of initial hypotheses (Mandinach et al., 2006). The next step is to summarize what has been analyzed. The summary of information should be directed by the initial objective of what the consumer hopes to achieve. The summary information could provide varying scenarios and dimensions to a particular problem. To produce knowledge, the decision-maker must synthesize or combine information and prioritize knowledge, often involving judgement based on the decision-maker's prior experiences (Siemens, 2014).

Prioritisation ranks the knowledge by importance, and hence the decision-maker can determine what areas require more focus than others (Mandinach et al., 2006). This then assists in identifying the appropriate decision to take, which can be implemented and the resulting impact monitored. The resulting impact can then be used to possibly initiate further tasks, such as further data collection, creating an iterative cycle which results in decisions (Mandinach et al., 2006). This data driven decision-making framework also highlights a cyclical process of data planning, data implementation and data assessment and analysis, also identified and supported by the Means, Padilla and Gallangher's Conceptual Framework for data driven decision-making (Means, Padilla, & Gallagher, 2010).

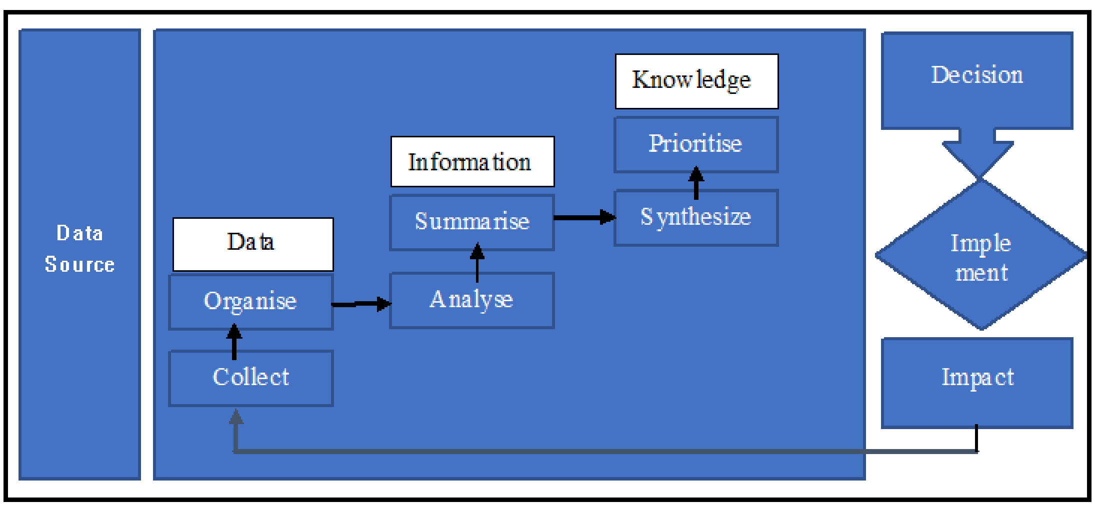

Figure 1. Framework for data driven decision-making (Mandinach et al., 2006)**.**

Executives wish to know that the data they are using is reliable, timely, and accurate (Sun, Luo, & Das, 2012). Trust theory supports the notion that the decision to place trust in something is driven by a person's mental attitude, prediction or evaluation of the item, the intention to delegate trust, as well as the behavior or intentional act of trusting (He, Lai, Sun, & Chen, 2014). Factors such as motivation, willingness, ability, "know-how", a person's self-confidence, beliefs, opportunities, dangers, obstacles, and safety all impact on a person's decision to trust (Castelfranchi & Falcone, 2010).

Discrepancies between the data source and data store, over or understated data values, inconsistent or inaccurate data calculations, inconsistent data formats, data unavailability, and a lack of infrastructure to fulfil new requirements were cited as significant data issues affecting the ability to trust and use data (Marshall & De la Harpe, 2009). Therefore, when presenting data, data source and pipeline accuracy, data definition and structure consistency, timely retrieval and data support are vital considerations for data trust and use (Akerkar & Sajja, 2016).

In terms of organizational decision-making, a framework known as the Cynefin framework identifies five domains, each representing a situation in which an organization may be faced with (Snowden & Boone, 2007). Figure 2 provides a view of these five domains, namely, complex, chaotic, complicated, simple, and disordered (Gorzeń-Mitka & Okręglicka, 2014). The center domain represents disorder which represents the unknown (Czinki & Hentschel, 2016). Per the Cynefin framework, executive strategic decisions typically fall within the complex domain, due to the lack of clear cause and effect of the decision, as potentially new terrain is being explored (probed) and querying (of data) is required for information purposes. Therefore, the link between data and strategic decision-making, based on the characteristics of the complex domain, becomes apparent (Axelrod, 2015).

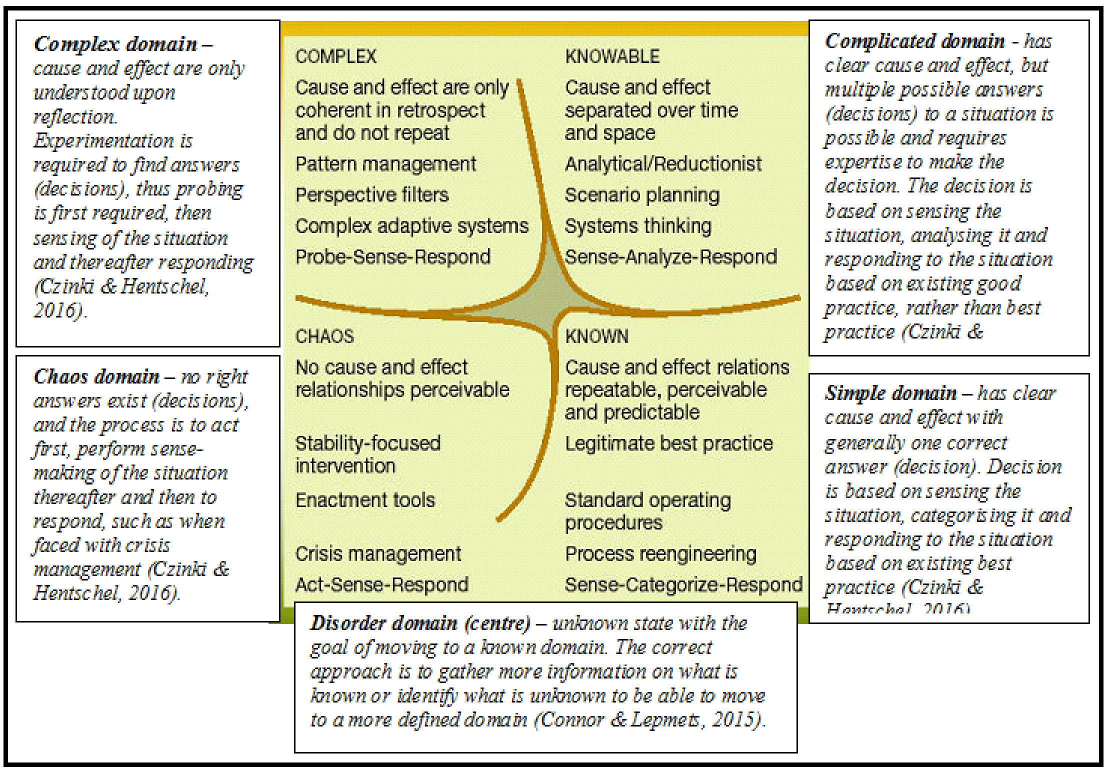

Figure 2. Cynefin framework for decision-making (Snowden & Boone, 2007)

Having reviewed the evolution of data and its challenges, questions come to light that require further explanation, including what role can information technology play to commence sense-making in a world where complexity is commonplace? How can corporate executives use big data in their role as visionary leader and strategic implementer? A popular solution is data visualization. Data visualization is a methodically developed graphic which represents data in a manner that allows one to obtain insights, develop understanding, identify patterns, trends, or anomalies faster, and promote engaging discussions (Dasgupta et al., 2015). Data visualization has been widely used as a tool for aiding understanding of complex phenomena by using technology to integrate graphic creation with image understanding and enabling more efficient communication (Wang, 2015).

Literature has stated, however, that visualization development faces challenges, including adequate viewer interaction, to enable the connection between data and human intuition (Teras & Raghunathan, 2015). Therefore, data visualizations are often not "fit-for-purpose"; in other words, they do not adequately guide executive decision-making. Today, data visualization is used within organizations to enhance the decision-making process (Toker, Conati, Steichen, & Carenini, 2013). As visualization is a tool promoting understanding, it enhances the link between visualization and sense-making (de Regt, 2014). In relation to big data, which adds another layer of complexity, data visualization is significant in presenting and communicating complex data intuitively by assembling and summarizing various forms and amounts of data for effective human information interpretation (Campbell, Chang, & Hosseinian-Far, 2015; Dasgupta et al., 2015; Gatto, 2015). Data visualization assists with sense-making by extrapolating meaning from complex datasets and uses the human visual system in order to create insight regarding conceptual information (R. E. Patterson et al., 2014; Reilly, 2013). The human visual system consists of the eye and a portion of the brain. The eye acts as a camera taking the picture, while the brain performs complex image processing allowing an individual to make sense of what has been seen (Nercessian, Panetta, & Agaian, 2013).

Thus, in summary, the benefits of visualization are knowledge sharing by externalizing internal understanding, improving thinking capacity, and assisting in new idea formulation by lessening the working memory of a person, and visualization can also create deeper relationship understanding (K. Li, Tiwari, Alcock, & Bermell-Garcia, 2016). This directly correlates to the data driven decision-making framework identified in Figure 2 (Mandinach et al., 2006), which highlights summarizing and analyzing as cognitive functions that must be applied to derive meaning from data.

Cognition is a mental process of information gathering and processing that aids reasoning and thus relates to sense-making (Helfat & Peteraf, 2015). Cognitive fit theory (CFT) and the proximity compatibility principle (PCP) can be used to explain how data visualizations can be effective for decision-making. PCP describes how related information must be shown or grouped together (Russ et al., 2014). PCP relates to the problem-solving task as task proximity and representation as display proximity (Murata & Akazawa, 2014). CFT explains how best to present data in order to solve a problem effectively (John & Kundisch, 2015). The cognitive fit theory states that the problem-solving task, such as solving a strategic complexity, and the problem representation of the task involved, such as a data visual, contribute to the effectiveness of the problem-solving process (van der Land, Schouten, Feldberg, van den Hooff, & Huysman, 2013). The interaction between the problem-solving task and the problem representation creates a mental representation in the mind of the decision-maker, leading the decision-maker to solve the problem faster and more accurately when the problem representation fits the problem-solving task (Teets, Tegarden, & Russell, 2010). The cognitive fit theory identifies that a decision-maker uses two predominant tasks, the symbolic task and the spatial task (Dilla & Raschke, 2015). The symbolic task involves extracting very accurate and granular data values, whereas the spatial task reflects a holistic view of the problem and considers other factors such as subjective data (Pournajaf, Xiong, Sunderam, & Goryczka, 2014; Vessey, 2006). The spatial task requires the decision-maker to formulate relationships between data elements, whereby perception plays a significant role in defining these relationships (Vessey, 2006). Supplementing cognition is perception which uses the eye for understanding and interpretation purposes (Prinz, 2010). The cognitive fit theory's use of spatial and symbolic tasks reflects the process of strategic decision making by executives, as executives use both objectivity and subjectivity to make strategic decisions (Teets et al., 2010).

Individual user characteristics, such as cognitive abilities, also impact on the ability of the individual to consume data visualizations (Szabo & Klein, 2014). Cognitive abilities include perceptual speed (speed when performing perceptual tasks), visual working memory (storage and manipulation capacity of visual and spatial information), verbal working memory (storage and manipulation capacity of verbal information), personality traits including locus of control (extent to which an individual believes that events are determined by their actions or by external forces), and, finally, visual and domain expertise on interactive data visuals (preferential choice) (Acheson, Hamidi, Binder, & Postle, 2011; Dane, Rockmann, & Pratt, 2012; Koop & Johnson, 2013; Lefcourt, 2014; Luck & Vogel, 2013; Nettelbeck & Burns, 2010). Visual design is not focused on creating 'pretty pictures', but is rather centered on providing information that has relevancy and purpose for the task at hand. If the data visual does not display relevant information, the visual output could lead to confusion, frustration and incomprehension (K. Li et al., 2016). Further research into the use of images in information systems research noted that images inherently include knowledge that is relevant to the subject at hand, and it is this knowledge that aids analysis, rather than the visual form itself (Andrade, Urquhart, & Arthanari, 2015). Do data visualization design elements, such as color, size, and data grouping affect user performance? To test such a premise, an experiment was conducted whereby participants were asked to find a target within a visual (Gramazio, Schloss, & Laidlaw, 2014). Two experiments were conducted, one using a scatterplot and one depicting squares within a grid. A scatter plot displays variables plotted against axes in a graph, whereby potential correlations can be viewed (Baarz & Cowan, 2013).

A grid allows multiple data to be displayed in a tabular format, creating the ability to sort, drill into, or exclude data for decision-making (Farhangi, 2010). The results of the scatterplot and grid experiments concluded that color layout, quantity, and size of the marks impact on visual search time, impacting user performance (Gramazio et al., 2014; Ware, 2012).

Guidelines to enhance optimal visualization design have been identified, namely grouping similar marks and colors together. Secondly, spatial ordering of marks in relation to the number and size of visual marks also impacts user performance (Gramazio et al., 2014).

Based on the literature reviewed, a condensed view of the principles of effective graphics is identified in Table 3.

Table 3. Principles of Effective Graphics (Hegarty, 2011)

Principle	Principle Explanation
The Proximity Compatibility Principle	More integrated tasks are facilitated by displays that are high in display proximity; more focused tasks are facilitated by displays that are low in display proximity.
The Relevance Principle of Graphics	Present no more or no less information than is needed by the user.
Principle of Capacity Limitations	Displays should be designed to take account of limitations in working memory and attention.
Apprehension Principle Principle of Discriminability	A visual display has to be accurately perceived. Present animations at a speed that can be apprehended and use visual dimensions that are accurately judged. Visual forms indicating a difference between two variables should differ by a large enough amount to be perceived as different.
Principle of Compatibility	A visual display is easier to understand if its form is compatible with its meaning.
Principle of Salience Principle of Informative Changes	Design displays to make the most important thematic information salient. Avoid large changes in properties of a display that do not carry information.
Principle of Appropriate Knowledge	Ensure that the viewer has the necessary knowledge to extract and interpret the information in the display.
Principle of Visual Momentum	Code multiple displays consistently and provide visual aids to help users make referential connections between different displays and avoid disorientation in animated and interactive displays.

FINDINGS

While research has been performed regarding the elements of good visualization design and its current success within the realm off big data, little research has been performed in understanding the use of data visualization to optimize the executive strategic decision-making process from the perspective of executives. In order to establish further insight into the requirements of executives for effective and efficient data visualizations, as well as the practical implications of the literature reviewed, semi-structured interviews were conducted with 13 executives and 4 data analysts in relation to the 3 research questions.

RQ1: What do individual organizational executives value and use in data and data visualization for strategic decision-making purposes?

Based upon the findings, to answer RQ1, organizational executives must first be clear on the value of the decision. No benefit will be derived from data visualization if the decision lacks value. The executive also stressed the importance of understanding how data relevancy was identified, based on the premise used by the data visualization developers. Executives also value source data accuracy and preventing a one-dimensional view by only incorporating data from one source. Hence the value of dynamism, or differing data angles, is important. In terms of the value in data visualization, it must provide simplicity, clarity, intuitiveness, insightfulness, gap, pattern and trending capability in a collaboration enabling manner, supporting the requirements and decision objectives of the executive. However, an additional finding also identified the importance of the executive's knowledge of the topic at hand and having some familiarity of the topic. Finally, the presenter of the visualization must also provide a guiding force to assist the executive in reaching a final decision, but not actually formulate the decision for the executive.

RQ2: How does data visualization impact on executives' ability to use and digest relevant information, including on their decision-making speed and confidence?

Based on the findings, to answer RQ2, themes of consumption, speed, and confidence can be used; however, the final themes of use and trust overlap with consumption, speed and confidence. Consumption is impacted by the data visualization's ability to talk to the objective of the decision and the ability of the technology used to map the mental model and thinking processes of the decision-maker. Furthermore, data visualizations must not only identify the best decision, but also help the executive to define actionable steps to meet the goal of the decision.

Executives appreciate the knowledge and skill of peers and prefer an open approach to decision-making, provided that each inclusion is to the benefit of the organization as a whole. Benchmark statistics from similar industries also add to the consumption factor. Speed was defined only in terms of the data visualization design, including using contrasting elements, such as color, to highlight anomalies and areas of interest with greater speed. Furthermore, tolerance limits can also assist the executive in identifying where thresholds have been surpassed, or where areas of underperformance have occurred, focusing on problem areas within the organization. Finally, confidence is not only impacted by the data visualization itself but is also affected by the executives knowledge of the decision and the factors affecting the decision, the ability of the data visualization presenter to understand, guide, and add value to the decision process, the accuracy and integrity of the data presented, the familiarity of the technology used to present the data visualization, and the ability of the data visualization to enable explorative and collaborative methods for decision-making.

RQ3: What elements must data analysts consider when developing data visualizations?

Based on the findings, to answer RQ3, the trust theme identifies qualitative factors, relating to the presenter. The value, consumption, and confidence themes all point to the relevance of having an open and collaborative organizational culture that enables the effective use of data visualization. Collaboration brings individuals together and the power of knowledgeable individuals can enhance the final decision. In terms of the presenter, his/her organizational ranking, handling of complexity and multiple audience requirements, use of data in the data visualization, ability to answer questions, his/her confidence and maturity, professionalism, delivery of the message when presenting, knowledge of the subject presented, understanding of the executive's objectives and data visualization methodology, creation of a "WOW" factor, and understanding the data journey are all important considerations.

CONCLUSION

Findings from this research study can provide practical knowledge for data visualization designers, but can also provide academics with knowledge to reflect on and use, specifically in relation to information systems (IS) that integrate human experience with technology in more valuable and productive ways. Academics can explore new ways of data processing and product design and development, while focusing on the distinct relationship between human cognition and IS.

Based on the literature review performed, much of the data visualization research appeared in the health sciences industry, with little reference to data visualization effectiveness in corporate environments. Further research within the IS field can include the effects of corporate culture on data visualization use. Corporate culture is a concept that describes the corporate's ethos, which has not been clearly referenced or defined in prior data visualization literature (Schein, 2009). This research study did however identify that a collaborative culture can affect the decision-making process and that data visualization must be able to open the communication channels in order to be effective. However; questions remain. If the corporate culture is dominant and autocratic, can data visualization still serve as an effective decision-making tool? In these instances, could data visualization bridge the gap between varying organizational strategies and employees to enhance corporate collaboration? Can data visualization still be effective in non-data driven environments? The researcher also became aware of the importance of human cognitive and sensory processes and its impact in IS development. The researcher believes that more focus can be placed on the psychological factors of technology acceptance. The current TAM model, used to describe use in this research study, identifies perceived usefulness and perceived ease-of-use as the primary considerations in technology adoption. However, factors that have been identified that impact on use do not express the importance of cognitive processes in technology adoption. For example, this research has identified mental modelling as a key consideration in limiting user fatigue, but how does this translate into technology design and acceptance? The purpose of information systems is to enable a richer, more productive and enabling experience for users. Technology trends are oftentimes developed from an idea generated from a single person, who pushes the technology solution onto people without consideration of the effects on human behavior. However; as users become more technologically intelligent, the trend may turn to where users drive the technology development based on the interactions and experiences they would like to have. Therefore, IS should also focus on the intangible factors that can affect adoption and technology use. Future research studies can be designed to explore answers to these questions.

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