People Analytics webpage

For me, \*\*people analytics\*\* refers to data-driven practices that help improve organizations and their workforce. But analyzing data about people at work is nuanced, complex, and can be challenging.

For most organizations, advancing people analytics may predicate a strong data culture. In contrast, many organizations may struggle with limited transparency of HR data to advance people analytics. Also, fully embracing people analytics may require partnering with finance and technology teams – it’s not just an ‘HR thing.’

My professional interest is in helping HR teams improve data literacy, for example, to advance analytical thinking at work. And in my experience, so many HR teams struggle with data literacy in ways that translate data into insights than in turn drive actions.

When we start with people analytics, we often end with a better understanding of organizations.

I began my career in workforce analytics in 2003 (before \*people analytics\* entered our vocabulary, see chart).

My professional interest is in helping HR teams improve data literacy, for example, to advance analytical thinking at work. One way to achieve this is through leveraging best practices in data visualization to foster the *showing of data* and the *thinking of data*.

Best Practices in Data Visualization

There are numerous resources to learn about data visualization practices. As the popularity of data visualization has grown, new online communities have thrived. For example, the Data Visualization Society (see [datavisualizationsociety.com](https://www.datavisualizationsociety.com)) shares best practices within its community. It helps its members collaborate and develop new skills. Also, publications such as *The* *New York Times*, *The Economist*, and *Scientific American* have dedicated resources online to help advance data literacy through journalism (see [nytimes.com/column/whats-going-on-in-this-graph](https://www.nytimes.com/column/whats-going-on-in-this-graph), [economist.com/graphic-detail](https://www.economist.com/graphic-detail), and scientificamerican.com/department/graphic-science). Although it may be beneficial to collate a comprehensive list of data visualization best practices in a paper such as this, this is not the purpose of this chapter. However, this section includes guidelines and best practices useful when designing or evaluating data visualizations.

Many data visualization practices aim to facilitate the transfer of information and to increase comprehension of the topic. Also, practices may intend to guide the viewer (i.e., to not mislead). Some may say there are many design principles to consider when creating data visualizations. But as noted earlier, how one interprets information may depend on the quality of the data presentation (Thomas & Cook, 2006; Zhu, 2007). Undoubtedly, many factors make it challenging to establish *the* best practices to apply for every data visualization.

Data Literacy

Workingwith data and speaking with data are critical skills for a data literate society. Data literacy skills may include data-driven problem-solving skills such as asking the right questions, identifying relevant (and valid) data, creating easy-to-understand visualizations, and influencing decision makers to take action based on the results of the analysis.

This paper suggests that numeracy and graph literacy are related to data literacy. Both numeracy and graph literacy are fundamental components of data literacy. However, data literacy may include additional knowledge, skills, and abilities beyond numeracy and graph literacy. For example, the ability to extract meaning from data and to communicate findings is an essential data literacy skill for analysts. Improving data literacy may begin with numeracy and graph literacy but includes other skills and abilities. For example, data management skills and statistical literacy are also foundational components of data literacy. Likewise, data stewardship, data governance, and data privacy may also relate to data literacy. However, data literacy skills for many business professionals may be limited, and many organizations may face challenges with low literacy in a data-driven world. One implication for practice from this study is improving data literacy skills in the human resources function.

People Analytics

As organizations strengthen capabilities in data science, data analysis skills are also needed in the human resources (HR) function. In general, this function is referred to as *workforce analytics*, but also *HR analytics*, *talent analytics*, *human capital analytics*, and *people analytics* (Huselid, 2018). A recent SHRM-SIOP white paper, based on interviews with practitioners, provides context for the skills and resources needed to build an analytics function (Kaur & Fink, 2017). Similarly, as the HR function becomes more aligned with the business, the need for evidence-based HR and people analytics will continue to grow (Ulrich & Dulebohn, 2015). The effective communication of analytical findings may help manage human capital better, improve organizational decision making, and drive business strategy. A growing number of universities now offer programs and classwork in people analytics. See Appendix N for links to these resources. Many of the programs vary in scope and differ based on the goals of the student and school. However, all the programs share an objective in developing data literacy and analytical skills for HR professionals.

Companies such as Netflix, Facebook, and Google have developed expertise in people analytics and promote practices in organizational studies. Google shares resources on people analytics on *re:Work* (see [rework.withgoogle.com/subjects/people-analytics](https://rework.withgoogle.com/subjects/people-analytics/)). For example, one guide, *How to Adopt an Analytics Mindset*, outlines the steps on how to tell a story with data: To develop a compelling, action-oriented story, one should (a) know the preferences of the audience, (b) keep the presentation short and succinct, and (c) focus on the context, findings, and call to action. There are many resources available online for workforce analysts to improve their expertise and, in general, drive data literacy throughout their teams and organizations.

Career Opportunities

Growth in data science has come from people – analysts, programmers, statisticians – who use technology to generate data-driven insights. And although data scientists are effective in analyzing large datasets, some data scientists may experience challenges in communicating data-driven insights (Donoho, 2017). Businesses are recruiting data scientists with data visualization skills for their HR functions. For example, at Netflix, qualifications include experience with *analytical tools to support data analysis, reporting and visualization* to c*reate visualizations that make data insights easily digestible*. At Facebook, one may apply *expertise in people research, quantitative analysis, and data visualization* to help *recruit, select, grow, and retain talent*. Furthermore, at Capital One, the data scientist designs *rich data visualizations to communicate complex ideas to customers or company leaders*. See Appendix O for details. Lastly, data science skills are also needed for psychological research (Chen & Wojcik, 2016; Harlow & Oswald, 2016). In summary, data visualizations skills, and in general a high level of data literacy, may be important for psychologists working within human resources functions.

Final Remarks on Data Science and HR

Many businesses consider the ability to extract meaning from data and communicate findings to stakeholders as a critical skillset (Dykes, 2016). These challenges apply to HR professionals and IO psychologists as well (Poeppleman & Sinar, 2017; Tonidandel et al., 2015). Furthermore, as opportunities in workforce analytics grow, more organizations may benefit from applying data science methods in their HR function (Batt & Banerjee, 2012; Bersin et al., 2016; Ulrich & Dulebohn, 2015). Organizations use data to make better decisions and use data visualizations to communicate analytical findings to decision-makers (Davenport & Patil, 2012). Developing a better understanding of how to best deliver analytical results to leaders with different levels of numeracy and graph literacy may help improve the overall effectiveness of the analytics function (Grant, 2018; Keen, 2018). However, as data visualization methods vary, the presentation of analytical findings will differ as well.

In summary, this study set out to address the need for more research in data visualization practices, especially for the benefit of the HR analytics functions. Still, more empirical research is needed to build the credibility of the data visualization field and to establish empirically tested practices in data visualization. An agenda for future research is needed. Likewise, many best practices are being used when developing data visualizations. This implication is discussed in the *Agenda for Future Research* section in this chapter.

Agenda for Future Research

The premise of this study – how analytical findings are presented and perceived – was a rich topic and provided a range of opportunities. This study, and other research on cognitive processes (such as perception, attention, memory) associated with data visualization, may help explain how to improve cognitive tasks such as comprehension. Also, the study of cognitive tasks such as reasoning, sensemaking, and understanding may have an ever-growing association with data visualization practices. However, more empirical studies are needed.

Prior research explored how cognitive style related to data visualization format. Engin and Vetschera (2017) found that data presented in a table reflected a decrease in errors for participants with an analytical orientation. In contrast, data presented in tabular form to participants with an intuitive orientation reflected an increase in errors. This study found that numeracy and graph literacy related to data comprehension. However, future studies may need to control for other factors such as cognitive style, such as analytical versus intuitive orientation when examining data visualization practices. One hypothesis to explore is whether individuals with an analytical orientation will perform better using tables compared to individuals with an intuitive orientation when controlling for SNS and SGL levels.

Other hypotheses to explore is whether other types of data visualizations, for example, line charts or statistical graphs, associate with data comprehension differently. Additional studies may focus on the number of data points presented in the visualizations. Also, studies may consider assessing the objective of the data visualization rather than assessing comprehension. For example, studies may focus on evaluating data visualization practices that relate to effective action-orientated situations or outcomes. New research may assess whether participants make the best inference and arrive at the best conclusion using different data visualization practices.

Additional opportunities for future research may focus on gaining a better understanding of how individual differences, such as data visualization preferences, prior experience, and learning, may vary by individual. For example, Maltese et al. (2015) found that graph comprehension increased with the participants’ academic level. Future studies may explore which data visualization practices help younger students strengthen their data literacy skills. The suggestion here is to look at additional constructs and the broader set of competencies associated with *data literacy* oreven the broader scope of the *analyst archetype*. Two promising areas for future research include (a) studies related to a theoretical framework for data comprehension, and (b) studies related to a theoretical framework for evaluating data visualizations. New theories on the data visualization methods and practices may be needed to build and enhance the theoretical frameworks associated with data visualizations.

There may be an endless list of questions to explore related to data visualization practices, especially as more organizations become data savvy. Moreover, as technology evolves, new research opportunities may develop. For example, future work in data visualization may include using machine learning practices (e.g., image recognition) to train models. Machine learning would create algorithms on the mechanisms of cause and effect of data visualization practices. In contrast, artificial intelligence would apply these algorithms into models. Likewise, advances in data visualization research may drive new technologies, such as artificial neural networks, which corresponds to human cognition. In the end, a community of practice may form a better understanding of the data visualization features and practices that relate to improvements in cognition. Fortunately, there is an ever-growing group of data enthusiasts who follow trends and best practices in data visualizations. These communities can help shape an agenda for future research in data visualization practices.

Conclusion

This study, and the existing literature associated with data visualization practices, were weaved together to address four key questions. This research, through the lens of cognitive psychology, may contribute to future research in the data visualization field.

A summary of the answers to the four key questions posited in this paper follows:

1. Data comprehension varied based on data display mode; tables were associated with higher data comprehension (significant difference in one of the two scenarios).
2. Data comprehension was associated with best practices in data visualization; applying best practices to a stacked bar chart was associated with higher data comprehension.
3. Data comprehension correlated with subjective numeracy (SNS); on average, participants with High SNS had higher data comprehension than participants with Low SNS. However, data comprehension for participants with Low SNS was similar to (as high as) participants with High SNS when viewing data in the best practice chart that was used in one scenario.
4. Data comprehension correlated with subjective graph literacy (SGL); on average, participants with High SGL had higher data comprehension than participants with Low SGL (significant difference in one of the two scenarios).
   1. However, participants with Low SGL had higher data comprehension than participants with High SGL when viewing data presented as a best practice chart that was used in one scenario.
   2. Also, participants with High SGL, on average, had the highest data comprehension score when viewing data presented in the best practice table.

A central finding of this study is that participants’ SNS and SGL levels correlated positively with data comprehension. Also, this study found that presenting data in tables was associated with higher data comprehension. Lastly, findings suggest that creating best-practice tables and charts related to improvements in data comprehension, especially for individuals with low subjective numeracy or low subjective graph literacy.

In closing, it should be noted the idea for this study developed naturally given the popularity of data visualizations and the recent growth of data science within the industrial-organizational psychology field. Some may say these are exciting times in data visualization. Alberto Cairo, in his foreword in *Data Visualization in Society,* states, “field X reaches maturity when a parallel field of ‘philosophy of X’ springs into existence. That hasn’t happened yet with data visualization, at least formally” (Cairo, 2020, p. 17). Cairo goes on to state that “writing about visualization doesn’t mean just thinking about how to design visualizations, but also about what visualization is, why it is the way it is—and what it could be” (Cairo, 2020, p. 17).

Moreover, the focus on data visualizations helps reinforce the notion of the *showing of the data* and the *thinking* *of the data* to foster analytical thinking. Tufte’s (1997, p. 53) quote remains relevant: “Clear and precise seeing becomes as one with clear and precise thinking” (p. 53). The philosophy of data visualization may foster a culture of analytical thinking. The analytical thinking mindset may help strengthen mental models of evidence, inference, and conclusions. By advancing analytical thinking, psychologists may find opportunities to improve data-driven decision-making processes in organizations.

Many in the analytics community can benefit from a better understanding of how to create useful data visualizations, why they are what they are, and about their uses. However, more research is needed, especially as data visualization practices continue to advance.