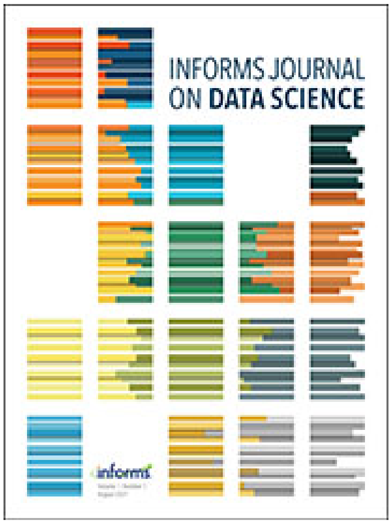


INFORMS Journal on Data Science

Publication details, including instructions for authors and subscription information:
http://pubsonline.informs.org

Visualization in Operations Management Research

Rahul Basole, Elliot Bendoly, Aravind Chandrasekaran, Kevin Linderman

informs
http://pubsonline.informs.org/journal/ijds
INFORMS JOURNAL ON DATA SCIENCE
Articles in Advance, pp. 1–16
ISSN 2694-4022 (print), ISSN 2694-4030 (online)

Visualization in Operations Management Research

Rahul Basole,[a] **Elliot Bendoly,**[b] **Aravind Chandrasekaran,**[b] **Kevin Linderman**[c]

[a] Accenture AI, Atlanta, Georgia 30308; [b] Operations and Business Analytics, The Ohio State University, Columbus, Ohio 43210; [c] Penn State University, State College, Pennsylvania 16801

Contact: rahul.basole@accenture.com, https://orcid.org/0000-0002-7328-5276 (RB); bendoly.2@osu.edu, https://orcid.org/0000-0002-0158-8403 (EB); chandrasekaran.24@osu.edu (AC); kevinlinderman@psu.edu (KL)

Received: January 25, 2021
Revised: June 11, 2021; August 15, 2021
Accepted: August 30, 2021
Published Online in Articles in Advance: November 17, 2021

https://doi.org/10.1287/ijds.2021.0005

Abstract. The unprecedented availability of data, along with the growing variety of software packages to visualize it, presents both opportunities and challenges for operations management (OM) research. OM researchers typically use data to describe conditions, predict phenomena, or make prescriptions depending on whether they are building, testing, or translating theories to practice. Visualization, when used appropriately, can complement, aid, and augment the researcher's understanding in the different stages of research (theory building, testing, or translating and conveying results). On the other hand, if used incorrectly or without sufficient consideration, visualization can yield misleading and erroneous claims. This article formally examines the benefits of visualization as a complementary method enhancing each stage of a broader OM research strategy by examining frameworks and cases from extant research in different OM contexts. Our discussion offers guidance with regard to researchers' use of visual data renderings, particularly toward avoiding misrepresentation, which can arise with the incorrect use of visualization. We close with a consideration of emerging trends and their implications for researchers and practitioners as well as recommendations for both authors and reviewers, regardless of domain, in evaluating the effectiveness of visuals at each stage of research.

History: Rema Padman and Kwok Tsui served as senior editors for this article.

Keywords: data visualization • operations management • methods

1. Introduction

Like many disciplines, the field of operations management (OM) critically relies on data and empirics to generate theoretical and practical insights (Singhal et al. 2018). Similar to other fields, contemporary OM researchers have also increasingly been gaining access to data sets of greater size and scope, made possible by advancements in digitalization of processes, products, services, and systems; data technologies (e.g., data platforms, application programming interfaces, the (industrial) internet of things); and computing power (e.g., supercomputers, high-performance clusters, quantum computing). As a recent example, Bartel et al. (2019) used more than 1.8 million patient hospitalization records to investigate the relationship between hospital stay and 30-day mortality. Using larger data sets presents new opportunities and also poses several data challenges (e.g., missing data, quality, half-life, and censoring) that can result in misrepresentation if not managed well (Araz et al. 2020). More to the point, failure to address these challenges can result in biased results and incorrect conclusions (Bendoly 2016). To this end, OM researchers, such as those in other fields, have started to make use of sophisticated and interactive visualizations to help them better understand and use data (cf. Shmueli et al. 2006, Buono et al. 2007, Paroutis et al. 2015, Hamister et al. 2018).

Visualization is a scientific approach involving the graphical representation of data in order to allow individuals to see and understand trends, patterns, and outliers in data (Tufte 1983, 2006; Few 2009; Bendoly and Clark 2016; Ertug et al. 2018; Tay et al. 2018; Basole 2019a; Kirk 2019). Though critics have implied otherwise, visualization is far more science than art. Another common misperception is that data visualization is only an "alternative" and "less quantitative" approach to conveying information. This viewpoint has fundamentally limited its perceived relevance for researchers in fields such as OM. In reality, and particularly relevant to fields that study the structure, dynamics, and performance of processes and systems, visualization has the potential to accomplish what words and numbers alone cannot. Consider, for example, the holistic interpretation of a complex supply chain, knowledge exchange network, healthcare system, or process map. Words and numbers alone cannot capture either the structure or dynamics of such systems (Trier 2008, Harle et al. 2012, Zhang et al. 2015). Without a holistic view, researchers and managers alike risk focusing on the parts, making piecewise decisions and failing to fully consider the larger system (Nestorov et al. 2019).

A good visual rendering, in other words, can help translate data into information, providing valuable and actionable insights otherwise left unseen (Chen et al. 2012, Zhang et al. 2012, Beynon-Davies and Lederman 2017, Basole 2019b, Kurpjuweit et al. 2019). In a number of cases, scholars have specifically leveraged effective visualization to navigate through the various stages of research, including theory development, theory testing, and the translation of research results into meaningful practical insights and follow-on discussions (Van de Ven 2007). In contrast, poorly conceived and inappropriate applications of visualization, particularly if aesthetically attractive, may foster considerable biases in interpretation (Card et al. 1999, Szafir 2018). Even simple missteps, such as omitting a comparative critical benchmark or using inconsistent scaling, may result in flawed conclusions from the data. Our chief concern, which we elaborate upon, is that, with the increased ubiquity of visualization packages (e.g., Tableau, PowerBI, ggplot2, Matplotlib, etc.), researchers may err and fall subject to misinterpretation by way of convenient, albeit incorrect, applications of readily available visualization practices at various stages of research in OM as well as in other fields of study. The purpose of this article is to communicate the opportunities as well as the challenges when incorporating visualization methods into research cycles. Specifically, in this article, we shed light on two questions: How can visualization help researchers across key stages of empirical research? What biases and risks do scholars face when employing visualization techniques in their research?

To answer these questions, we begin by illustrating how visualization can be used across three broad but distinguishable stages of research: (1) theory/model development, (2) theory/model testing, and (3) translation/conveyance. We do so by drawing on our own firsthand experiences as editors and authors, having written and reviewed numerous studies of complex processes and systems for which the visualization of data has been critical. Our discussion makes use of examples from product design, healthcare operations, and operations strategy. These illustrative examples help provide some level of depth and specificity, highlighting research needs and rationales for the visualization approaches chosen along with the subsequent benefits derived. Following this discussion, we turn to a more generalized discussion of the common biases that may develop from misusing (i.e., poorly conceiving and rendering) visualizations. We draw connections to Gestalt psychology and cognitive science and outline how these issues might be mitigated through the careful design of visuals in support of each research stage. Ultimately, it is our hope that this discussion helps advance the application of visualization as an analytical resource for all those conducting practice-oriented research in the field of OM and beyond.

2. Visualization and OM Research Cycles

One point we reiterate throughout this paper is that visualization holds far more potential than simply providing a supporting role in research papers and final reports. The application of visual representations can contribute to the direction research takes as it unfolds. It can inspire data collection efforts necessary to fill critical gaps in analysis. It can serve as a vehicle to support claims or question the adequacy of preexisting assumptions. It can even facilitate the development of theory, new models, research questions, and hypotheses. These contributions further have the potential to benefit from one another with visualization facilitating feedback loops between theory, analysis, and translation.

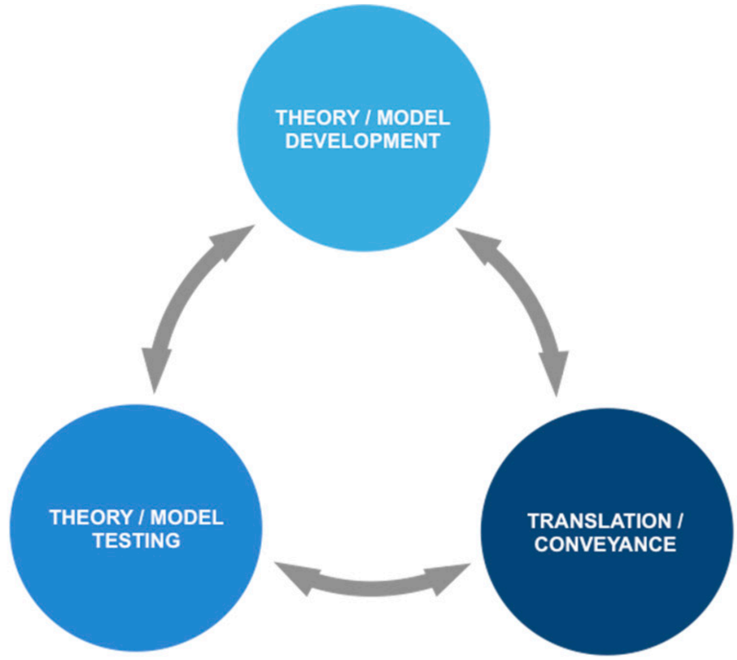
Figure 1 depicts the three generalized stages of research cycles common to OM and other management and social science disciplines with emphasis on the interrelated nature and opportunities for feedback among the stages (Van de Ven 2007). These stages involve theory/model development, theory/model testing, and translation/conveyance. This structure also aligns with the taxonomy by Sodhi and Tang (2014) with development and testing emblematic of the framing/modeling and testing stages outlined by these authors. Although visualization has an obvious role in the translation/conveyance stage, our depiction in Figure 1 emphasizes that visual awareness is a phenomenon relevant to all three stages of OM research. Indeed, we argue that this applies to most empirical research in various disciplines, including management, information systems, and applied engineering to name a few. Further, although feedback between visualization efforts at each of these research stages may vary greatly by research context, such interaction can also prove invaluable in augmenting awareness, given the distinct nature of inquiry at each stage and the mix of individuals potentially involved.

Figure 1 also gives an overview of the specific benefits and challenges associated with visualization at each of these respective stages. To expand upon these impacts and issues, in the sections that follow, we first consider the broad nature of perspectives, expressed by scholars in data science, OM, and other fields, on the best uses of visualization in research. We then leverage specific examples to connect the potential of visualization at each of the stages in Figure 1.

2.1. Perspectives on Visualization

To gain a full appreciation of the amplified primacy of data visualization in research, one needs to look at the various efforts made to advance these discussions across academic disciplines and industries in recent years (cf. Friendly 2008, Rees and Laramee 2019). Reviews of data visualization examples and generalized

Figure 1. (Color online) Visualization in OM Research Cycles: Goals, Consumers and Challenges



	THEORY / MODEL DEVELOPMENT	THEORY / MODEL TESTING	TRANSLATION / CONVEYANCE
Goal / Objectives of Visualization	Identify gaps for theory / new model forms to bridge	Check / validate assumptions built into models	Facilitate dialogue regarding findings and/or theory
Primary Consumer of Visualizations Created	Internal audience (researcher / research team)	Internal audience (researcher / research team)	External audience (practice and research community)
Challenges in Effective Use	Sufficient depth and breadth for theory mapping / scrutiny	Appropriate detail, form for objective assessment	Clarity and inclusion of critical details for practical use

tactics for the display of data can be found in diverse literatures, such as computer science, design, and software engineering (cf. Jena 2017, Peña et al. 2017, Chawla et al. 2018), bioinformatics (O'Donoghue et al. 2018), public health (Preim and Lawonn 2020), transportation (Chen et al. 2015), logistics (Wang et al. 2019), business (Roberts and Laramee 2018), finance (Ko et al. 2016), and sports (Perin et al. 2018).

Other studies examine the breadth of visual representation techniques and interactive dynamics used in visuals (Heer et al. 2010, Heer and Shneiderman 2012). In the data science space, reviews such as those by Joy (2009) and Khalid and Zeebaree (2021) focus specifically on the rise of algorithmic approaches to facilitating large-scale data access and processing for visualization. Niche reviews of cutting-edge advancements in visualization techniques and technologies continue to uncover emerging considerations, such as the applications of augmented reality in big data visualization (Chandra et al. 2019), trust in machine learning (Chatzimparmpas et al. 2020), the inclusion of multivariate graphs (Nobre et al. 2019), and potential caveats for future use (Howarth and Costello 1997, Olshannikova et al. 2015).

More specific to the interests of the OM research community, Lou et al. (2020) review data visualization applications in the field of supply chain management. Their discussion, like those of many contemporary reviews, showcases scholarly accounts in which tools and visual solutions are proposed. Unsurprisingly, the visualization examples they present are typically oriented either toward capturing network structures (Vliegen et al. 2006, Goh et al. 2013, Singh et al. 2019) or business process flows (Sackett and Williams 2003, Sulek et al. 2006, Urabe et al. 2019). Such depictions can successfully employ numerical and/or text data and annotations in conveying holistic representations of challenges and opportunities in supply chains, particularly when dynamic visual interfaces are augmented with interactivity (Liu et al. 2012).

Each of these reviews showcases a range of examples and technologies in which the visualization focus tends to be on the variety of artifact forms over the occasional deep dive into their technical function. It typically is emphasized, or assumed prima facie, that having "some" form of data visualization is superior to the absence of such rendering when making complex decisions. In the biomedical field, for example, O'Donoghue et al. (2018) provides commentary on the paucity of visual tools used by clinicians, drawing a connection to physicians' cognitive processing errors and misdiagnoses (Hegarty 2011, Craft et al. 2015). Indeed, the view that data visualization is a means to augment cognitive processing that is not easily replicated by text and numbers alone is shared broadly by cognitive psychology researchers (cf. Defeyter et al. 2009).

Yet, as important as these points may be for conveying the critical value of visualization (Thomas and Cook 2005, Keahey 2013, Ryan 2016, Ware 2019), review studies frequently shy away from providing the specific rationale behind the adoption of visualization techniques or the specific steps taken in the development of the features of visual artifacts presented as solutions. That is, the focus of these discussions tends to reside with the features of translation and conveyance (Figure 1) disconnected from the critical research processes that precede this stage. For instance, very little knowledge exists on how the visualization of data can assist researchers as they plan studies, look for best-fit theoretical frameworks, build models, and develop tools and metrics. We know less still about how the visual examinations of assumptions supported by test data have shifted with the examination of these tools in their prospective usage environments or whether these have led to specific modifications of the proposed artifacts. In short, although the benefits of adopting the right type of visual renderings during each stage of the research process can be sizable, actual discussions into application across these stages is lacking.

In addressing this, our interest is to offer insights into the specific relevance of visualization and visual design considerations to all stages of research (Figure 1) with particular focus on our experience with the OM discipline. We consider examples from three domains emblematic of recent OM research growth and with the potential to illustrate visualization activities specific to the stages outlined in Figure 1: management of innovation, healthcare operations, and operations strategy. Each domain has departmental representation at top-level operations journals (in some cases, multiple department representation), and each has been the subject of multiple domain-specific reviews and commentaries (cf. Boyer et al. 2005, Anand and Gray 2017, Kavadias and Ulrich 2020, Koskinocak and Savva 2020). Although many other critical domains comprise OM scholarship, exemplars focusing on these three domains are sufficiently representative to inspire extrapolation to others.

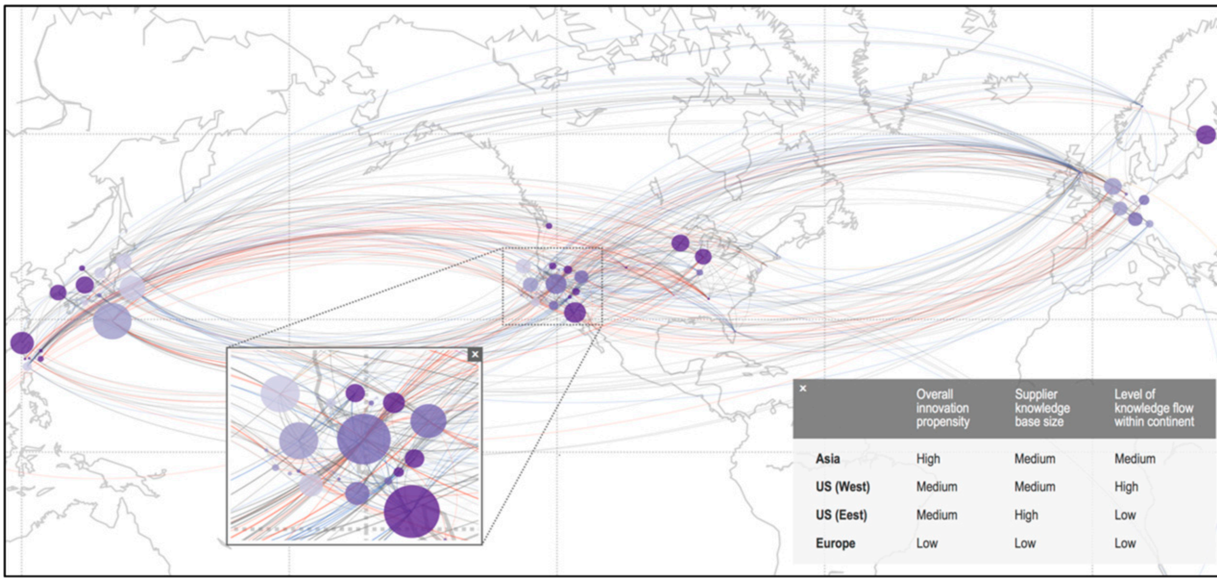
2.2. Theory/Model Development

Within this stage, researchers face the task of formulating theoretical associations and distinctions. This includes not only identifying factors and directions of cause-and-effect relationships, but also complex multidimensional, nonlinear, and contingent relationships (cf. Sampson 2012). The visualization of data, whether drawn from empirical observation or derived analytically, can pinpoint opportunities for deeper consideration at this stage, particularly in contexts in which theory is emerging (Langley and Ravasi 2019).

Ideally, both practice and extant research inform the development of future research, inspiring new practice-relevant questions. Thus, contributing to theory requires identifying underexplored areas in which researchers need to examine richer contextual settings and gain further understanding regarding the boundary conditions. Visualizing data on preexisting theoretical structures and related findings can help reveal opportunities and encourage spanning across existing theoretical and conceptual domains. It may inspire alternative models of reality for theoretical consideration. Visual exploration of large-scale data sets can also unveil contemporary dynamics that may have been overlooked in prior research but appear increasingly salient to operational contexts. This, in turn, can inspire the development of new theoretical arguments. The identification of trends that deviate from existing theoretical discussions would certainly warrant closer introspection, just as deviations from anticipated results can motivate post hoc explorations and subsequent theoretical examination. Therefore, although the visualization of data in this stage can be highly suggestive of enhanced predictive capabilities that novel theory and models might provide, the nature of visualization work in this stage is predominantly descriptive. Its intent is typically to reveal rich details, static or dynamic, that can inspire research questions and hypotheses for testing rather than attempting to provide confirmation (a matter for the next stage).

From a tactical standpoint, in the use of visualization toward these ends, there are many different visual layouts that can provide the rich descriptive analytics that support theory and model development. For instance, a graph-based geographic layout of supply chain networks can encode firms as nodes and position them using latitude/longitude coordinates (Zhu and Watts 2010). This approach can provide a clear geographic footprint of the network as well as highlighting interconnections between spatially distributed teams working in different firms (see Figure 2, from Basole et al. 2017). Visual differentiations across these nodes, by size, color, and connection to others in the visual field, can be used to encode additional, multidimensional details. From this vantage point, geographic anomalies (e.g., political or physical barriers to connectivity) can

Figure 2. (Color online) Network Layout Depicting Geographic Footprint and Global Interconnectivity (from Basole et al. 2017)



be identified and used to refine broader theoretical arguments through practical discussions of moderation effects. Ultimately, these can be instrumental in setting up testable hypotheses that are likely to cut through significant noise.

By way of illustration, let's consider one example from the Basole et al. (2017) study on global supply chain networks in the context of highly dynamic industries. Ideally, supply networks enable effective and economic movement of products, are structurally robust to cope with disruption, and facilitate knowledge sharing and collaboration between partners to pursue opportunities and anticipate risks. Yet not all supply networks are the same. In fact, in their study Basole et al. (2017) find that supply network characteristics vary widely, depending on firm size, industry, geography, and life cycle. Geospatially distributed graph visualizations of these networks for one particular firm, along with node color and size encoding of key attributes, reveal that, although one network had a substantive supply base in the U.S. West, marked by a tightly interconnected between-supplier knowledge base, some of its highest concentration of knowledge capital (innovativeness) actually resided in Asia. Reliance on important knowledge sources for value creation outside the home country can have serious performance implications for a focal firm. This important theoretical insight might have gone unnoticed had the authors failed to use proper visual rendering.

Graphing the geographic footprint, firm interconnectedness, and firm innovativeness allowed these authors to better develop theory regarding their inquiry into supply chain networks. Specifically, visualization helped in the following manner: (1) The geospatial distribution of structural and knowledge risk across firms became apparent. (2) The unbalanced clustering of firms within and across regions was revealed, suggesting that firms may utilize core–periphery supply chain network structures. (3) The strength of connectivity between and within geographic regions was highlighted with a significant dependency on Asian suppliers, raising issues of robustness and resilience against localized disruption. (4) The relative weakness of connectivity and innovation capital by European suppliers is exposed, suggesting potential supplier-switching opportunities. (5) Colocation of knowledge capital near the focal firm in the U.S. West was revealed, raising issues of salient knowledge concentration.

Although each of these observations is drawn from a single type of visualization and by no means are research questions in themselves, they provoke theoretically interesting questions: Why is the network structured this way? Why are there regional distinctions? What are the implications of this structure? In particular, we can point to the core–periphery observation (point 2), which, drawing on network theory, might suggest a power differential or a leader–follower structure. If that is the case, theoretically, one might argue that actions taken by the leader in one period are likely followed by those on the periphery in subsequent periods. Researchers might carry this insight forward into formal investigation by developing associated hypotheses and further normative or empirical examinations.

Theoretical discussion could also form around the weak connectivity observation specific to Europe (point 4). Agility and the ability to avoid technical lock-ins could signal opportunities for step gains in innovation for firms more active in Europe given the more ample switching opportunities. More broadly, one might suggest that individual firm differences in

Figure 3. (Color online) ACO Tile Grids of Integrated Care, Readmission Performance, and Colorectal Screening (Contiguous United States, from Lan et al. 2022)

network positioning, increasingly proximal to weak connectivity regions of a network map, might offer unique innovation and revenue opportunities for firms. Thus, visualization can yield observations as well as novel theoretical considerations, arguments, and research questions and, at the same time, support for further statistical and computation analysis.

2.3. Theory/Model Testing

In the model testing stage of research, researchers evaluate the strength of theoretical arguments and model structures based on collected data and/or assumed distributions. Visualization can be used to provide confirmation and understanding of the robustness of model assumptions by evaluating theories and complex process dynamics across multiple dimensions (Delias et al. 2019). It can also assist with consensus seeking when the best approach to interpreting data is in question (cf. Tarakci et al. 2014, Peng et al. 2019). Holistically, if some of the baseline assumptions fail (e.g., regarding the nature of data continuity, linearity, distributions, and overall quality), one must reconsider how data can be used to test hypotheses posed or may have to consider changes to models used for testing. This applies to both confirmatory support of highly normative models as well as the estimation of effects in less constrained empirical models.

Although statistical tests can provide a great deal of insight into both model fit and appropriateness, they can also miss structural issues or fail to capture structural anomalies. That, in turn, can undermine the practical predictive power of the models. As an example, consider a researcher studying how healthcare innovations such as accountable care organizations (ACOs) affect overall health outcomes (e.g., readmission risk and preventive health behavior). The objective of ACOs is to integrate care across the continuum (primary care, hospital, and postacute care) and ensure better patient outcomes (screening outcomes and readmissions) for the panel of patients. Figure 3, based on data from Lan et al. (2022), provides two comparative tile grid maps of ACOs within the United States. In this case, the choice of a tile grid map as opposed to a choropleth is motivated by the fact that differences in state size can impart a confounded depiction of key relationships. By distinguishing outcomes along a color gradient (heat mapping), scaling the size of a tile to depict coverage, and including smart labels, the visual encodes multiple variables of interest simultaneously. It facilitates the detection of outliers and missing values while enabling rapid, straightforward comparisons. In this depiction, one can discern that states with highly integrated care also tend to have (i.e., are predictive of) higher cancer screening rates and lower 30-day hospital readmissions.

Another interesting trend that might be supported by a similar approach is the possible link between ACO adoption and a region's political tendencies. The ACO was part of the Affordable Care Act championed by the Obama administration, and states that had a strong Democratic voter presence when the program was implemented have tended to favor promoting ACO mandates over time. In this same study, heat mapping revealed that gubernatorial elections presented a likely exogenous shock (and, hence, a potential instrument), which, in turn, could be incorporated into an analysis of the health system's view toward adopting ACOs (i.e., without affecting the health systems' performance). Being able to overlay a range of related details while leveraging proximal and holistic structures of a system exemplifies the interpretive strengths of heat map depictions, which continue to motivate their use in various OM settings as well as in other disciplinary contexts (cf. He et al. 2019, 2020; Konitzer et al. 2019). In short, visualization in this instance and others provides a window into the enhancement and predictive abilities of the theoretical models under consideration.

2.4. Translation/Conveyance

In the translation/conveyance stage, researchers work to communicate ideas, data, and findings to external audiences, often those in practice. In some instances, this is done with the very deliberate intent of obtaining additional data of a particular nature from those audiences that can serve as a catalyst for future research. Because these presentations are, by definition, translations of relatively complex considerations, they are almost certainly piecewise representations (Comi and Whyte 2018, Franco and Greiffenhagen 2018). Further, just as piecewise theoretical considerations and analytical examinations are limiting albeit unavoidable at least to some degree, these presentations can also be misleading.

The associated risk is augmented by the fact that so much latent understanding can go uncaptured. This, in turn, can give a false impression of codependencies and dynamics to those external audiences and can undermine trust between the researcher and practice. Proper use of visualization allows researchers to overcome these deficiencies. In Hardcopf et al. (2017), visual renderings are used iteratively with case interview protocols. Both computer-generated and hand-drawn exercises assist in model validation exercises (cf. Figure 4). These combined descriptive, predictive, and critically prescriptive efforts also inspire the generation of subsequent data (via feedback from external audiences), which, in turn, feed additional stages of model refinement. Although a technically simple approach, the authors demonstrate the power of visually enhanced engagement efforts to drive critical input and improvements through a didactic and integrated research cycle.

As suggested, in this stage, potential prescriptions, built on predictive and descriptive experience, must be brought to the foreground for practical application (cf. advanced control chart and cumulative sum applications proposed by Sukchotrat et al. 2011 and Shu et al. 2008, respectively). Such positioning is also critical so that the relevance of such applications can be properly scrutinized and improvements to theory and modeling achieved. Indeed, in Hardcopf et al. (2017), engagement with practitioners in the examination of preliminary model findings was paramount. In the absence of flexible visual renderings, it would have been all but impossible for all parties to have gained comparable awareness; the interactive visual artifacts helped translate complex system dynamics into an evolutionary depiction of the system's behavior over time.

2.5. Visualization Capabilities and Benefits

These research examples show visualization's unique capabilities for each stage of the research cycle that may not be possible using other traditional approaches alone. To emphasize both the capabilities of visualization (relative to other analytical tactics) as well as the benefits these capabilities can yield, it is worth reviewing these by research stage. Table 1 gives a summary of the benefits that visualization yields in these stages as illustrated in the examples discussed.

Looking at these capabilities and benefits, one might ask whether the extent to which each can be realized depends greatly on the nature of the data in question. The answer must of course be "yes." The nature of data ultimately drives what is possible through its visualization. In certain types of data, the distinctions in benefits and challenges associated with extracting these visualization benefits can be notable. For example, two of the most common forms of data considered in a typical analysis are (1) cross-sectional and (2) longitudinal data. Both forms of data share many of the same challenges and prospective benefits provided by the capabilities offered in visualization. In many cases, both cross-sectional and longitudinal data may in fact be intertwined in simultaneous consideration. However, each form or aspect of that data

Figure 4. (Color online) Causal Loop, Practitioner Corrections, and Results from Adjusted Models (from Hardcopf et al. 2017)

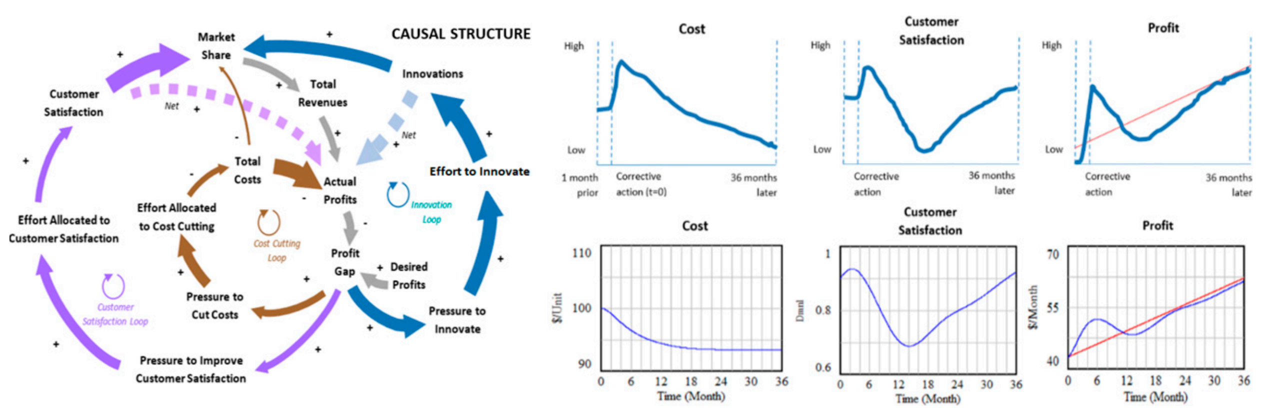


Table 1. Capabilities and Benefits of Visualization Across Stages of Empirical OM Research

Stage	Visualization capabilities	Visualization benefits
Theory/model development	Explore, identify, and portray structures and dynamics in data distributions that may not be encapsulated either in words or by a finite set of numerical summary measures. Reduce the dependency of data examination on preexisting assumptions regarding its structure and behavior.	Describe areas of insufficient theoretical understanding or opportunities to span theoretical arguments and suggest causal linkages. Enhance the grounding for novel theory and model development.
Theory/model testing	Capture the potentially complex structure and dynamics variation from developed theory and model designs. Confirm (or find flaws in) the holistic nature of baseline assumptions central to such theory and model designs.	Identify the conditions under which observations deviate the most from predictions derived and opportunities for nuanced theory and model modification to account for such conditions, adding clarity to predictions or fundamentally changing key aspects of models.
Translation/conveyance	Convert implicit knowledge and analytical experience of researchers regarding prescriptions to external audiences, acknowledging the potentially distinct vantage points held by those audiences. Create opportunity for engagement with those audiences to facilitate feedback.	Enhance the scrutiny of assumptions, derived inferences, and model prescriptions. Increase face validation and practical relevance.

can offer its own sets of challenges in the path toward effective visualization.

One key distinction emerges from the units of analyses that are common to each. Cross-sectional data analysis often leverages nominal (e.g., firm, state) or categorical (e.g., industry) distinctions or some form of nested structure (e.g., firm within industry). Just as in nonvisual analytical approaches, the emphasis given to each data point, and the categorical grouping of such points, must be considered carefully so as to not confound messaging. This is one of the reasons behind the selection of appropriate visual encodings, such as critical data-driven size and color distinctions in the points visualized in Figures 2 and 3 and why state boundary geometries are not used. However, the caution applied to aggregation in cross-sectional data spans all stages of the research cycle.

In the case of longitudinal data, with which a primary focus tends to be on ordinal or interval data analysis, the unit of aggregation in time (e.g., minute, day, year) presents parallel cautions albeit distinct in form. Greater granularity in time avoids the risk of missing critical dynamics (e.g., accounting for autocorrelation in measures of interest) yet also raises the specter of excessive noise clouding the ability to distinguish signals of phenomena in the data. For this reason, it is often valuable to permit user flexibility (i.e., interactivity) in the visualization of alternate time frames and scales. This is perhaps most immediately critical to the first two stages of the research cycle (theory and model building and testing). Yet such flexibility can also prove valuable in inspiring dialogues with academic and practitioner audiences when present in the conveyance of results. Visual representations specifically designed for longitudinal data can help alleviate potential issues and provide the ability to reveal and communicate temporal patterns of interest across all stages (Aigner et al. 2007).

Broadly speaking, both longitudinal and cross-sectional data evaluations share more commonalities than differences when it comes to challenges and best practices in data visualization (e.g., safeguarding against omissions, clarity in scale presentation, etc.). Both benefit from multidimensional perspectives and flexibility in vantage points. Both benefit from a strong consideration of the audience that the visual is intended to inform and the purpose that the visual is attempting to accomplish. Further, the capabilities and benefits of visualization at each stage of research cycles may be observed regardless of whether the core attribute of the data is cross-sectional or longitudinal. To that end, it is reasonable to expect that the same set of critical questions one might ask regarding the effectiveness of a given visual should prove applicable in either case. We return to what some of these questions might be later in our discussion.

3. Common Challenges When Using Visualization for Empirical Research

Each stage of the research cycle entails different needs, data resources, audiences, and challenges. As such, each may benefit from distinct visualization approaches. Beyond focusing on fit between data, visual form, and purpose in these research stages, researchers must bear in mind the kinds of risks that inadequate visuals can create. In particular, we find two common misrepresentations that may arise when creating visualizations: (1) misrepresentation by omission and (2) misrepresentation by inclusion. Misrepresentation by omission involves the insufficient portrayal of the systems or subsystems under examination through the exclusion of key features in visual renderings. Clearly such misrepresentation poses a threat to any aspect of the research effort; visualization is no exception. Misrepresentation by inclusion, in contrast, involves the portrayal of superfluous content that distracts from, masks, or distorts key aspects of the systems or subsystems under visual examination. Although often viewed as a lesser concern, such inclusions can nonetheless result in incorrect conclusions as well, and hence, caution must be exerted as to how and when to include various factors during visualization.

To help provide some guidance to researchers and practitioners, it may be useful to think about examples of misrepresentation. Table 2 gives an overview of the two types of misrepresentation and the associated concerns across the three analytical dimensions of visualization research. This framework emphasizes the relationship to the three analytical purposes of description, prediction, and prescription, which may prove relevant to all stages of research. As seen from Table 2, concerns specific to descriptive visualization tend to also apply to other purposes just as concerns relevant to predictive visualization apply to prescriptive efforts.

As shown in Table 2, a variety of common concerns apply to data scope and aggregation choices as well as choices in the structure of and supplemental documentation accompanying visual renderings. These considerations are present in almost any research context and can present themselves at each stage of research. Attention to each of these concerns should begin with descriptive efforts because misrepresentation in such

Table 2. Misrepresentation Concerns Across Analytical Purposes of Visualization

Analytical purposes of visualization	
Misrepresentation by omission	Misrepresentation by inclusion
Descriptive (core to theory/model development)	
Scope: Not including a comparative critical benchmark, reference line, or context for data (e.g., cropped axes, origin not starting at lowest value, missing categories such as gender that could give more information).	*Scope:* Including data beyond relevant consideration (e.g., time ranges prior to scope of interest), inconsistent axes scales for multiple charts, including information (e.g., location) that may reveal confidential information.
Aggregation: Over-aggregation of data (e.g., point averages presented without indications of variance, variance masked).	*Aggregation:* Under-aggregation of data (e.g., mark occlusion, inordinate grouping with groups of different size).
Structure: Not including data to describe completeness (e.g., percentages that do not sum to one, denoting missing data).	*Structure:* Using inconsistent or misleading scaling (e.g., data drive bubble radii, mixed scaling in multidimensional plots).
Supplements: Not including a legend (e.g., color, scale, mark), axes labels, axes upper and lower bounds, and units (e.g., omitting $ or %). Not including labels to critical data or data range distinctions.	*Supplements:* Including superfluous dimensions, colors and annotations (e.g., 3-D bar chart, mark shading without explicit meaning, nonrelevant labels, visual clutter/chart junk).
Predictive (core to theory/model testing)	
All above concerns apply	***All above concerns apply***
Scope: Not including factors known to affect outcomes (e.g., controls).	*Scope:* Superimposing factors that are theoretically distinct by affect outcomes.
Aggregation: Over-aggregation of results (e.g., not showing uncertainties in models estimates or risk/variability associated with modeled outcomes).	*Aggregation:* Under-aggregation of results (e.g., including nonsignificant factors in effect representation, occlusion across interpolated model plots).
Structure: Not providing model transparency (e.g., omitting significance of factors, contribution, interactions, etc.).	*Structure:* Emphasis of aspects of model structure not consistent with statistical contribution, including aspects untested.
Prescriptive (translation/conveyance)	
All above concerns apply	***All above concerns apply***
*Scope/aggregation/structure:*Not showing the full solution space (e.g., possible alternatives and risk associated with such alternatives).	*Scope/aggregation/structure:*Prescribing beyond the range of evidence, including solution benefits disproportionately to risks/costs.
Overarching	
Fit to research/audience: Not providing the right visual form to fit the needs of the research question, research stage, and associated audiences.	

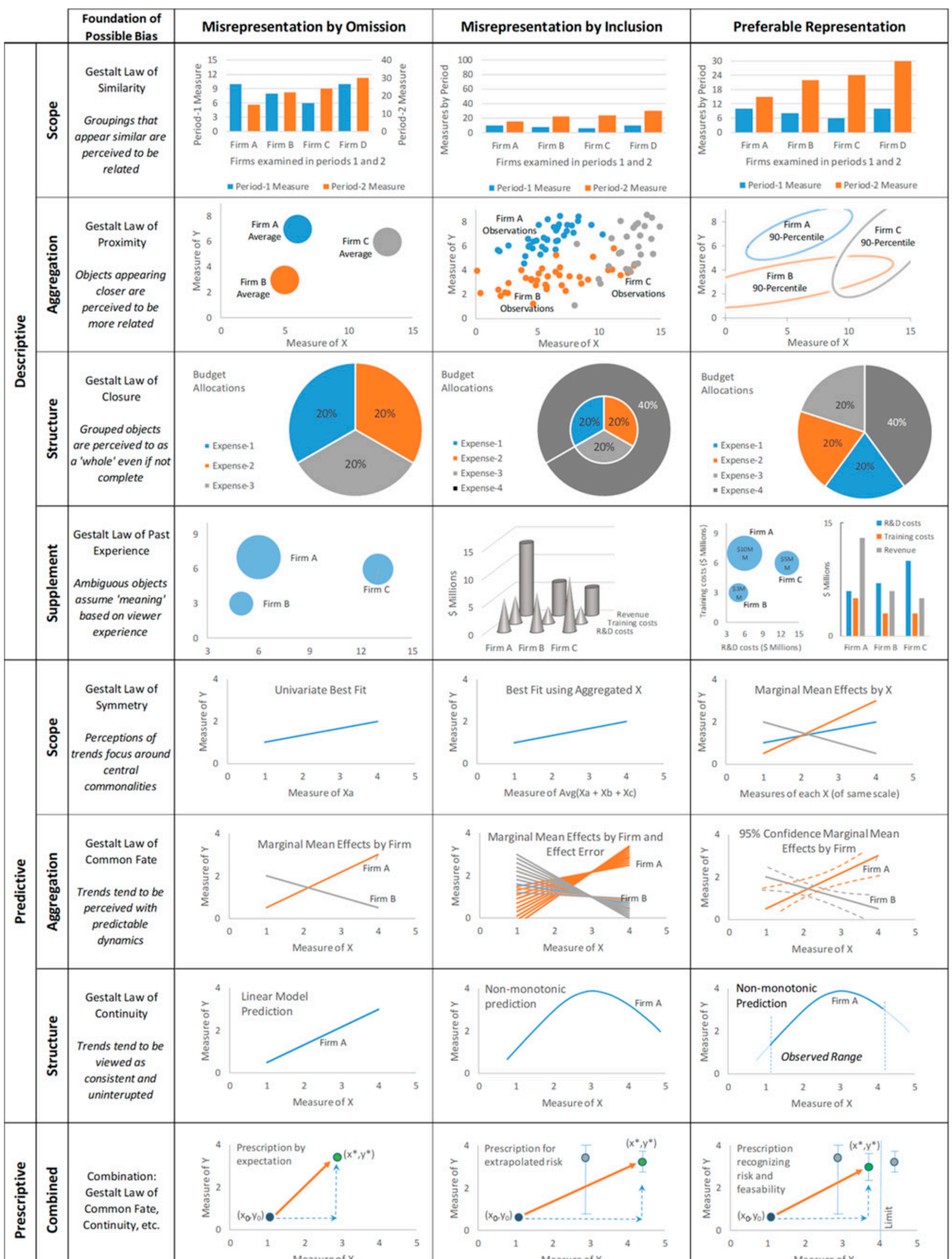
Note. The concerns are not comprehensive but are emblematic of major and common concerns.

efforts can plant seeds for misrepresentation in others. Fundamentally, the choice of a visual must meet the needs of the research, the stage in the research effort, and the associated audience. Ultimately, the simplest rule of thumb is to use the smallest irreducible set of factors needed for depiction and avoid including content that does not contribute to the research conversation at each stage (Bendoly and Clark 2016).

Figure 5 provides simple visual illustrations of each these misrepresentations along with preferred visual alternatives to such flawed depictions. The design of preferred alternatives should focus on minimizing the natural biases typical of human visual perception. Here, the "laws" outlined by classical Gestalt psychology (Koffka 1935), suggesting visual forms align with human perceptual tendencies, also describe why such tendencies can allow poor visual designs to mislead interpretation. Accordingly, we highlight examples of these laws that are likely to be the source of considerable bias and misinterpretation resulting from flaws in visual representation.

The structure of Figure 5 mirrors that of Table 2. Although visual renderings can aid each stage in the research cycle with interests serving descriptive,

Figure 5. (Color online) Illustrative Misrepresentations, Foundations for Bias and Solutions



predictive, and/or predictive analysis, there are pitfalls to both omitting key elements as well as including issues that obfuscate. For example, a descriptive analysis that attempts to contrast three potentially distinct sets of cases may oversimplify their distinctions by graphing measures of centrality alone (see descriptive-aggregation concerns in Table 2 and Figure 5 in the omission column). On the other hand, showing all the available data simultaneously in a single plot may provide a very different impression of such differences, suggesting that there may be only very little difference among these sets (the inclusion column). A more meaningful representation of distinction can be generated by plotting statistical confidence regions (e.g., confidence ellipses per blackbelt-apps.com) for each subset, thus permitting a consideration of the distribution of each in which differences are the greatest as well as when similarities exist. Without such a nuanced presentation, those viewing overly omitting or inclusive renderings may fall victim to set biases (Bendoly and Clark 2016), per the action of the Gestalt law of proximity, overgeneralizing the likelihood of distinctions or similarities and selecting subsequent analysis that does not sufficiently represent the reality of the data (e.g., treating each subsample as entirely distinct or disregarding notable distinctions that exist).

As an additional example, consider prescriptive analysis—often leveraged as a part of the research translation stage of cycles. Visually describing a path for performance improvement associated with changes in a decision that can be adjusted in practice can be greatly limited by the exclusion of information associated with the uncertainty that such a change might yield (i.e., the risk profile associated with a specific prescription). In fact, if risk is not sufficiently considered in analysis, prescriptions may not fit the risk tolerance of practitioners. Even if risk is considered, if a description of both the upside and downside associated with a prescription is not conveyed and included in comparison with the status quo and other options, practitioners may not be able to fully justify recommended changes (omission column of prescriptive). Doing so would be at their own peril. Further, changes in practice are not unbound. In particular, even if risk profiles for options are well rendered, if such renderings include options that extend beyond the reasonable scope of practice, their value can be overemphasized (inclusion column). Ensuring that the visual rendering of valuable options relative to the status quo includes risk but is limited to reasonable constraints of action is critical to the pragmatic understanding of prescriptions for both researchers and practitioners.

4. Trends and Future Directions

Our discussion to this point has focused on current opportunities and best practices in the use of visualization in OM research though we would be remiss to ignore several trends and future directions that are likely to make these points still more salient to our field as well as others. For discussion purposes, we broadly classify these emerging phenomena along two dimensions: (1) data available for visualization and (2) techniques available for visualizing data. We also discuss some of the continuing and emerging concerns resulting from these advancements in the field.

4.1. Trends and Directions in Data

The first dimension relates to the rapidly evolving landscape of data that is becoming relevant and accessible to OM researchers and, frankly, those in many other related fields. Across all existing and emerging OM domains (e.g., operations, supply chain, healthcare, innovation, strategy, technology management, policy, etc.), we can point to examples of this explosive growth. Driven by technological advances and increased digitization, firms are instrumenting all aspects of their enterprises at higher granularity. That they are doing so at significantly improved quality levels enables unprecedented opportunities for researchers to generate analyses and visualizations at multiple levels (people, process, organization, and ecosystem) (Basole et al. 2011, Rouse 2015).

The speed of generating, processing, and providing data has significantly improved as well. Past researchers may have had only batch-level data, receiving periodic, static data sets about OM-related domains of interest; today, these data sets are dynamically refreshed, approaching real time and streaming levels. Notable examples of well-fed OM data streams include performance of manufacturing systems, supply chain tracking and traffic, quality and safety trends, healthcare processes and health conditions, and customer behavior data.

Furthermore, we are seeing a much wider variety of data types becoming available to researchers. Alongside more common structured qualitative and quantitative data, OM researchers can now count on the increased generation and availability of unstructured data types (e.g., text, audio, images, video). For instance, product descriptions, customer reviews, and news articles can all be mined to discover competitive strategies and innovation of firms. Combined with improved computational capabilities, these emerging data types can be processed and mined at speed and scale; machine learning, image processing, and text analytics are just some of the technologies enabling insights into not only what happened, but also why and how. With this information, scholars are better able to account for cause and effect, predict alternative scenarios, and prescribe preventive strategies.

As the features of available data expand in these ways, the use of visualization techniques to make inference of these data has also evolved significantly. In what follows, we elaborate on these emerging trends in techniques and discuss the additional concerns arising as new visualization techniques are adapted across stages of research.

4.2. Trends and Directions in Techniques

A growing body of visualization research examines how to best represent uncertainty graphically, maximizing the accuracy of scholars' quantitative reasoning while reducing their audiences' cognitive burdens and, subsequently, the chances of misleading interpretation (Hullman 2019). Because uncertainties can be quantitative (e.g., economic growth) or qualitative (e.g., fail/not fail) in nature, visualization researchers concerned with representing uncertainty are experimenting with different techniques, including shading, transparency, confidence bands/ellipses, fuzziness, or different graphical markers (dotted versus solid lines). Similarly, temporal changes and evolution of research domains may require researchers to utilize uncommon representations and techniques, including connected plots, multiple snapshots (small multiples), animations, or traces.

From a more technical data science standpoint, increasingly popular is the use of artificial intelligence (AI) in image processing and visualizing. Chen et al. (2019), for example, show how AI can be used in the visual design process. Discussions along these lines are also surfacing in news media contexts (Merler et al. 2020). For instance, leveraging machine learning–based image processing and text analytic approaches on publicly available news and corporate data are poised to radically impact how managers make effective real-time decisions in the future. OM researchers studying service operations can now use tweets, chats, and other forms of unstructured data obtained during interactions with the service providers to visualize structure, sentiment, and abnormalities in conversations to guide interaction and predict when and what kind of products will be purchased by the customer. Similarly, healthcare OM researchers who are interested in studying the design of preventive care delivery models can now use information from inexpensive tests, such as an electrocardiogram, to extract and then visualize health data to study disease progressions, such as heart failures. They are additionally finding new ways to integrate electronic medical records data with data collected by wearable devices (think Fitbit or AppleWatch) to predict patient well-being and recommend the implementation of e-visits and wellness coaching routines.

The use of AI opens up a range of other potential possibilities. For instance, visuals can be personalized to different users to limit domain-specific biases. Using a visual to explain a concept to someone in healthcare could obviously be different than explaining the same concept in a retail setting. Assisted by evolving AI, scholars are able to create better targeted, customized visualizations, both extending the applicability of such visualizations and revealing underlying contingencies related to the practice. However, the use of AI in designing visuals has its own set of risks. Several practical examples caution its effectiveness in developing fake news (Dockray 2017). Scholars need to be careful not to engage in sophisticated techniques to strengthen claims that don't have merit.

By means of these techniques, researchers and practitioners can generate images based on a wide collection of documents. Such form of textual-to-visual transformation can help managers make effective real-time decisions but are also associated with newer challenges. For instance, AI visuals rendered from customer or patient data could also contain sensitive identifiable information that needs to be properly managed to protect confidentiality. In what follows, we elaborate a bit more on the emerging concerns that are arising as a result of the use of visualization techniques. We also discuss the strategies that can allow researchers to mitigate these concerns.

4.3. Continuing and Emerging Concerns

Although concerns over misrepresentation by inclusion or omission continue regardless of data and technique, the emergence of new data and techniques also raises the salience of certain specific concerns. Consider again the use of AI in image processing and visualization. Developments in this space, increasing the scope of prospective applications and users, also raise the specter of data breaches, personal information losses, and explicit data ethics violations (see Hirsch et al. 2020). To get a better sense of this risk, Hirsch et al. (2020) draws the connection between advances in AI, visual renderings from various data sources, and ultimately corporate decisions that are perfectly legal but unethical. One example in an emerging OM context involves the analysis of mobility information from autonomous vehicles. Given the geographically dispersed and dynamic nature of the context, a natural aspect of analysis would involve the development of static, dynamic, and/or potentially interactive visual mappings from automobile GPS. Such data contains information on customer travel patterns (e.g., shopping details that can be sold to other companies for marketing use) as well as driving behaviors (e.g., exceeding speed limits, which can be shared with the police).

Such data are sensitive at the unit level. Therefore, overly rich renderings, albeit technically available and potentially useful from a decision-making standpoint, threaten to create a backdoor privacy nightmare by allowing the reverse engineering of individual identification. Transparency is a virtue in data visualization, yet there must be upper bounds on the richness of visual inclusions. Basic tactics, such as avoiding "chart junk," certainly place functional bounds on inclusion per our discussion of misrepresentation; however, practitioners and researchers must also contend with ethical bounds. Such considerations should limit the number of simultaneous visuals and interactivity that might enable triangulation, reidentification, and personal data exposure. In line with Figure 1, this point highlights the importance of recognizing how various use cases also differ by visual consumer (Bhattacharjee et al. 2020).

Healthcare institutions and researchers are already taking additional steps to ensure protection of privacy and security of data and its visual forms. As an illustrative example, consider healthcare research into the role of patients' social determinates of health (e.g., mobility, access to food, etc.) on improving health outcomes. Scholars involved in this kind of research often use visual renderings on patient's home location, geographic proximity to a hospital, access to a grocery store, etc., and integrate this information with patient health data (e.g., number of primary care visits, A1c levels, body mass indices, and preexisting conditions) to obtain insights. Such forms of visual renderings may also result in unintentionally revealing patient home locations and other details (e.g., neighborhoods), which are patient personal information. Common data protection entities, such as universities' internal review boards (IRBs) are unable to evaluate the risks arising from data forms that could allow a motivated individual or entity to uncover private patient information. Thus, in addition to IRBs, health institutions are mandating the presence of separate committees, such as data trust and value committees to evaluate the benefits and risks of providing access to data and making visualizations and other interpretive representations available to outside audiences. These committees are made up of computer scientists, statisticians, and legal representatives able to anticipate and recommend solutions for such problems. In one case, a committee recommended the use of hashing algorithms and randomizing patient geolocations to a 1,000-meter distance in order to mask granular patient data.

Industry, too, has responded to the imperative to evolve best practices around advanced visualization as data sources and visualization techniques proliferate. Companies are beginning to establish separate data trust and privacy committees, and they have established new CXO positions, such that chief data officers and others are tasked with evaluating the use of advanced AI and visualization techniques to process unstructured forms of data. The question remains as to how quickly research institutions will integrate similar structures into their own institutional review structures.

5. Conclusions

This paper lays out the benefits of data visualization in a specific context: the stages of empirical research with illustrative examples drawn from OM contexts. As editors and reviewers of articles in OM, we repeatedly see researchers underutilize or incorrectly utilize visualization techniques in ways that result in biased or incorrect conclusions and interpretations. Rapid advancements in technical capabilities and equally rapid expansions of available data compound these problems without spurring an equal academic output regarding the ways visualization can help and hinder the development of theory, the process of model testing, and the correct and actionable translation and conveyance of scholarly insights to external audiences. We address this gap in the context of OM research with applications across disciplines, first, by outlining the unique benefits of visualization for three stages of the research process (see Table 1). Opportunities abound, yet visualization is simply one branch of methodology, intended to complement and not replace statistical or numerical analysis. Therefore, it is critical to emphasize that each stage of the research cycle faces different needs, data resources, potential audiences, and challenges and, hence, tends to see benefit from a different mix of visual and nonvisual approaches. Beyond focusing on fit between data, visual form, and purpose in these research stages, researchers must always bear in mind the kinds of risks created by inadequate visuals within each stage (see Table 2 and Figure 5).

The evaluation of any visualization is an iterative, continuous, and challenging human-centric process that requires a balancing of both subjective and objective criteria (Plaisant 2004, Munzner 2009, Isenberg et al. 2013, Wall et al. 2018). In the early stages of selecting, designing, and implementing visualizations, researchers must carefully assess their visual representation and interaction choices. Existing studies, for instance, provide guidance and guidelines of what visual representations are most effective for given data types and tasks (Cleveland and McGill 1984, Kelleher and Wagener 2011). Following these well-established data-to-visualization fit principles and guidelines is an important first step, but given the potential range of users and use contexts, visualizations should also be evaluated against other common metrics, including efficiency, comprehension, or insight (Stasko 2014). More recently, these metrics are also extended to more hedonic criteria, such as aesthetics, memorability, and engagement (Fu et al. 2019). With this in mind, we recommend that researchers ask critical questions of the visuals they construct at each stage of inquiry. Based on the categories of potential risks in misrepresentation presented in Figure 5, for example, the following questions can prove useful in identifying fundamental shortcomings to be addressed in visual renderings in the first stage of research cycles (theory and model development, as in Figure 1).

With regards to scope:

1. Does the visual clearly depict critical benchmarks to facilitate the identification of unexplored theoretical phenomena?

2. Are all axes scaled meaningfully to avoid under/overemphasizing differences that inform the identification of unexplored theoretical phenomena?

With regards to aggregation:

1. Does the visual use a level of aggregation that matches the level of analysis critical to facilitate the identification of unexplored theoretical phenomena?

2. Does the visual clearly distinguish groupings in terms of both measures of centrality and variation to facilitate the identification of unexplored theoretical phenomena?

With regards to structure:

1. Does the visual (or set of visuals) convey the interrelated nature of all critical dimensions to facilitate the identification of unexplored theoretical phenomena?

2. Does the visual (or set of visuals) capture critical cause–effect dynamics to facilitate the identification of unexplored theoretical phenomena?

With regards to supplements:

1. Does the visual clearly depict the scale and nominal differences of all dimensions depicted to facilitate the identification of unexplored theoretical phenomena?

2. Does the visual clearly depict bounds on data and phenomena to facilitate the identification of unexplored theoretical phenomena?

Each of these questions can be similarly applied to the second (theory/model testing) and third (translation/conveyance) stages of research cycles by substituting the terms "identification of unexplored" with terms such as the "confirmation of proposed" and "communication of assessed," respectively. Although we do not intend to suggest that these are the only critical questions to ask regarding the effectiveness of visual designs at each stage, they certainly provide a starting set catered specifically to research domains, such as OM and others with which we are familiar as scholars.

Finally, just as the development of research is often best characterized as iterative, the design of the best visual renderings similarly involves iterations between construction, scrutiny, and subsequent refinement. It should not be assumed that the first attempt to capture meaning in even the most fitting visual form will prove ideal. Yet overcoming our own personal biases in examining data by any means is one of the greatest challenges of research. Regardless of whether we are equipped with formal guidelines to help us narrow our decision space in visual design, there are still many options, just as there are always options in data collection, model structuring, and statistical estimation, beyond those choices that may appear fundamental. By purposely matching visual form with research purpose and with the likely priors of target audiences in mind (our own as well), we help mitigate the risk that these additional choices can undermine our overall efforts. At each stage of the research cycle, these needs change, and researchers must be willing to, in turn, reconsider the appropriateness of their renderings.

Fortunately, our own critical perspectives and efforts at diligence are not the only tools in our arsenal. One of the hallmarks of scientific theory and application development is the fact that progress never take place in a vacuum. Nor does it benefit from attempting to enforce one. Our audiences should not be regarded simply as eager receptacles of our knowledge at best. In the spirit of design thinking, they represent potential collaborators and sources of critical insight. At every stage of a research cycle, they present opportunities for constructive scrutiny and refinement in both our attempts to mathematically represent reality as well as to capture it visually. We encourage future research to leverage external audiences throughout the various stages of research and in iteration. To do so necessarily requires communicating information, understanding, and needs aided largely through visual rendering. If such renderings, serving the research–practice dialogue, became prevalent in research documentation, we believe that the culture of practice-oriented management research could shift markedly toward untapped levels of ethical impact.

References

Aigner W, Miksch S, Müller W, Schumann H, Tominski C (2007) Visual methods for analyzing time-oriented data. *IEEE Trans. Visualization Comput. Graphics* 14(1):47–60.

Anand G, Gray JV (2017) Strategy and organization research in operations management. *J. Oper. Management* 53–56:1–8.

Araz OM, Choi T, Olson DL, Salman FS (2020) Role of analytics for operational risk management in the era of big data. *Decision Sci.* 51(6):1320–1346.

Bartel AP, Chan CW, Kim SH (2019) Should hospitals keep their patients longer? The role of inpatient care in reducing postdischarge mortality. *Management Sci.* 66(6):2326–2346.

Basole RC (2019a) Strategy and structure: Visualizing complex ecosystems. Anand G, Gray JV, eds. *Keynote, 2019 DSI Annual Conf.* 53–56(1):1–8.

Basole RC (2019b) Visualization 4.0: The renewed relevance of visualization for business. *IEEE Comput. Graphics Appl.* 39(6):8–16.

Basole RC, Bellamy MA, Park H (2017) Visualization of innovation in global supply chain networks. *Decision Sci.* 48(2):288–306.

Basole RC, Rouse WB, McGinnis LF, Bodner DA, Kessler WC (2011) Models of complex enterprise networks. *J. Enterprise Transformation* 1(3):208–230.

Bendoly E (2016) Fit, bias, and enacted sensemaking in data visualization: Frameworks for continuous development in operations and supply chain management analytics. *J. Bus. Logist.* 37(1):6–17.

Bendoly E, Clark S (2016) *Visual Analytics for Management: Translational Science and Applications in Practice* (Taylor Francis/Routledge, London).

Beynon-Davies P, Lederman R (2017) Making sense of visual management through affordance theory. *Production Planning Control* 28(2):142–157.

Bhattacharjee K, Chen M, Dasgupta A (2020) Privacy preserving data visualization: Reflections on the state of the art and research opportunities. *Comput. Graphics Forum* 39(3):675–692.

Boyer KK, Swink M, Rosenzweig ED (2005) Operations strategy research in the POMS journal. *Production Oper. Management* 14(4): 442–449.

Buono P, Plaisant C, Simeonel A, Aris A, Shneiderman B, Shmueli G, Jank W (2007) Similarity-based forecasting with simultaneous previews: A river plot interface for time series forecasting. *11th Internat. Conf. Inform. Visualization* (IEEE, New York), 191–196.

Card SK, Shneiderman B, MacKinlay JD (1999) *Readings in Information Visualization: Using Vision to Think* (Morgan Kauffman Publishers, San Francisco).

Chandra ANR, El Jamiy F, Reza H (2019) Augmented reality for big data visualization: A review. *Internat. Conf. Comput. Sci. Comput. Intelligence* (IEEE, New York), 1269–1274.

Chatzimparmpas A, Martins RM, Jusufi I, Kucher K, Rossi F, Kerren A (2020) The state of the art in enhancing trust in machine learning models with the use of visualizations. *Comput. Graphics Forum* 39(3):713–756.

Chawla G, Bamal S, Khatana R (2018) Big data analytics for data visualization: Review of techniques. *Internat. J. Comput. Appl.* 182(21):37–40.

Chen H, Chiang RH, Storey VC (2012) Business intelligence and analytics: From big data to big impact. *Management Inform. Systems Quart.* 36(4):1165–1188.

Chen W, Guo F, Wang FY (2015) A survey of traffic data visualization. *IEEE Trans. Intelligent Transportation Systems* 16(6):2970–2984.

Chen L, Wang P, Dong H, Shi F, Han J, Guo Y, Childs P, Xiao J, Wu C (2019) An artificial intelligence based data-driven approach for design ideation. *J. Visual Comm. Image Representation* 61:10–22.

Cleveland WS, McGill R (1984) Graphical perception: Theory, experimentation, and application to the development of graphical methods. *J. Amer. Statist. Assoc.* 79(387):531–554.

Comi A, Whyte J (2018) Future making and visual artifacts: An ethnographic study of a design project. *Organ. Stud.* 39(8):1055–1083.

Craft M, Dobrenz B, Dornbush E, Hunter M, Morris J, Stone M, Barnes LE (2015) An assessment of visualization tools for patient monitoring and medical decision making. *IEEE Proc. Systems Inform. Engrg. Design Sympos.* (IEEE, New York), 212–217.

Defeyter MA, Russo R, McPartlin PL (2009) The picture superiority effect in recognition memory: A developmental study using the response signal procedure. *Cognitive Development* 24(3):265–273.

Delias P, Zoumpoulidis V, Kazanidis I (2019) Visualizing and exploring event databases: A methodology to benefit from process analytics. *Oper. Res.* 19(4):887–908.

Dockray S (2017) Fake news, artificial intelligence and data visualisation. *Artlink* 37(1):12–17.

Ertug G, Gruber M, Nyberg A, Steensma HK (2018) From the editors—A brief primer on data visualization opportunities in management research. *Acad. Management J.* 61(5):1613–1625.

Few S (2009) *Now You See It* (Analytics Press, Oakland, CA).

Franco LA, Greiffenhagen C (2018) Making OR practice visible: Using ethnomethodology to analyze facilitated modeling workshops. *Eur. J. Oper. Res.* 265(2):673–684.

Friendly M (2008) A brief history of data visualization. Chen C, Härdle WK, Unwin A, eds. *Handbook of Data Visualization* (Springer, Berlin), 15–56.

Fu X, Wang Y, Dong H, Cui W, Zhang H (2019) Visualization assessment: A machine learning approach. *Proc. IEEE Visualization Conf.* (IEEE, New York), 126–130.

Goh RSM, Wang Z, Yin X, Fu X, Ponnambalam L, Lu S, Li X (2013) RiskVis: Supply chain visualization with risk management and real-time monitoring. *IEEE Internat. Conf. Automation Sci. Engrg.* (IEEE, New York), 207–212.

Hamister JW, Magazine MJ, Polak GG (2018) Integrating analytics through the big data information chain: A case from supply chain management. *J. Bus. Logist.* 39(3):220–230.

Hardcopf R, Goncalves P, Linderman K, Bendoly E (2017) Short-term bias and strategic misalignment in operational solutions: Perceptions, tendencies and traps. *Eur. J. Oper. Res.* 258(3): 1004–1021.

Harle C, Neill D, Padman R (2012) Development and evaluation of an information visualization system for chronic disease risk assessment. *IEEE Intelligent Systems* 27(6):81–85.

He Y, Zhao Y, Tsui K (2019) Geographically modeling and understanding factors influencing transit ridership: An empirical study of Shenzhen metro. *Appl. Sci. (Basel)* 9(20):4217.

He Y, Zhao Y, Tsui K (2020) An adapted geographically weighted LASSO (Ada-GWL) model for predicting subway ridership. *Transportation* 48:1185–1216.

Heer J, Shneiderman B (2012) Interactive dynamics for visual analysis. *Comm. ACM* 55(4):45–54.

Heer J, Bostock M, Ogievetsky V (2010) A tour through the visualization zoo. *Comm. ACM* 53(6):59–67.

Hegarty M (2011) The cognitive science of visual spatial displays: Implications for design. *Topics Cognitive Sci.* 3(3):446–474.

Hirsch D, Bartley T, Chandrasekaran A, Parthasarathy S, Turner P, Norris D (2020) Corporate data ethics: Data governance transformations for the age of advanced analytics and AI. Preprint, submitted December 1, http://dx.doi.org/10.2139/ssrn.3828239.

Howarth P, Costello P (1997) The occurrence of virtual simulation sickness symptoms when an HMD was used as a personal viewing system. *Displays* 18(2):107–116.

Hullman J (2019) Why authors don't visualize uncertainty. *IEEE Trans. Visualization Comput. Graphics* 26(1):130–139.

Isenberg T, Isenberg P, Chen J, Sedlmair M, Möller T (2013) A systematic review on the practice of evaluating visualization. *IEEE Trans. Visualization Comput. Graphics* 19(12):2818–2827.

Jena B (2017) A review on data visualization tools used for big data. *Internat. Res. J. Engrg. Tech.* 4(1):492–494.

Joy KI (2009) Massive data visualization: A survey. Möller T, Hamann B, Russell RD, eds. *Mathematical Foundations of Scientific Visualization, Computer Graphics, and Massive Data Exploration* (Springer, Berlin, Heidelberg), 285–302.

Kavadias S, Ulrich KT (2020) Innovation and new product development: Reflections and insights from the research published in the first 20 years of *Manufacturing Service Operations Management*. *Manufacturing Service Oper. Management* 22(1): 84–92.

Keahey TA (2013) Using visualization to understand big data. *IBM Business Analytics Advanced Visualisation* 16.

Kelleher C, Wagener T (2011) Ten guidelines for effective data visualization in scientific publications. *Environ. Model. Software* 26 (6):822–827.

Khalid ZM, Zeebaree SRM (2021) Big data analysis for data visualization: A review. *Internat. J. Sci. Bus.* 5(2):64–75.

Kirk A (2019) *Data Visualisation: A Handbook for Data Driven Design*, 2nd ed. (Sage, London).

Ko S, Cho I, Afzal S, Yau C, Chae J, Malik A, Beck K, Jang Y, Ribarsky W, Ebert DS (2016) A survey on visual analysis approaches for financial data. *Comput. Graphics Forum* 35(3):599–617.

Koffka K (1935) *Principles of Gestalt Psychology* (Harcourt, Brace, New York).

Konitzer T, Rothschild D, Hill S, Wilbur KC (2019) Using big data and algorithms to determine the effect of geographically targeted advertising on vote intention: Evidence from the 2012 US presidential election. *Political Comm.* 36(1):1–16.

Koskinocak P, Savva N (2020) A review of healthcare-management (modeling) literature published in manufacturing and service operations management. *Manufacturing Service Oper. Management* 22(1):59–72.

Kurpjuweit S, Reinerth D, Schmidt CG, Wagner SM (2019) Implementing visual management for continuous improvement: Barriers, success factors and best practices. *Internat. J. Production Res.* 57(17):5574–5588.

Lan Y, Chandrasekaran A, Gordia D, Walker D (2022) Collaboration structures in integrated healthcare delivery systems: An exploratory study of accountable care organizations. *Manufacturing Service Oper. Management.* Forthcoming.

Langley A, Ravasi D (2019) Visual artifacts as tools for analysis and theorizing Zilber TB, Amis JM, Mair J, ed. *The Production of Managerial Knowledge and Organizational Theory: New Approaches to Writing, Producing and Consuming Theory* (Emerald Publishing Limited), 173–199.

Liu S, Zhou MX, Pan S, Song Y, Qian W, Cai W, Lian X (2012) Tiara: Interactive, topic-based visual text summarization and analysis. *ACM Trans. Intelligent Systems Tech.* 3(2):543–552.

Lou CX, Bonti A, Prokofieva M, Abdelrazek M, Kari SMC (2020) Literature review on visualization in supply chain and decision making. *IEEE 24th Internat. Conf. Inform. Visualisation* (IEEE, Piscataway, NJ), 746–750.

Merler M, dos Santos C, Martino M, Gliozzo A, Smith J (2020) Covering the news with (AI) style. Preprint, submitted January 5, https://arxiv.org/abs/2002.02369.

Munzner T (2009) A nested model for visualization design and validation. *IEEE Trans. Visualization Comput. Graphics* 15(6):921–928.

Nestorov S, Jukic B, Jukic N, Sharma A, Rossi S (2019) Generating insights through data preparation, visualization, and analysis: Framework for combining clustering and data visualization techniques for low-cardinality sequential data. *Decision Support Systems* 125:113–119.

Nobre C, Meyer M, Streit M, Lex A (2019) The state of the art in visualizing multivariate networks. *Comput. Graphics Forum* 38(3):807–832.

O'Donoghue SI, Baldi BF, Clark SJ, Darling AE, Hogan JM, Kaur S, Maier-Hein L, et al. (2018) Visualization of biomedical data. *Annual Rev. Biomedical Data Sci.* 1:275–304.

Olshannikova E, Ometov A, Koucheryavy Y, Olsson T (2015) Visualizing big data with augmented and virtual reality: Challenges and research agenda. *J. Big Data* 2(1):1–2.

Paroutis S, Franco LA, Papadopoulos T (2015) Visual interactions with strategy tools: Producing strategic knowledge in workshops. *British J. Management* 26(S1):S48–S66.

Peña LEV, Mazahua LR, Hernández GA, Zepahua BAO, Camarena SGP, Cano IM (2017) Big data visualization: Review of techniques and datasets. *Sixth Internat. Conf. Software Process Improvement* (CIMPS, Zacatecas, Mexico), 1–9.

Peng C, Lurie N, Slaughter S (2019) Using technology to persuade: Visual representation technologies and consensus seeking in virtual teams. *Inform. Systems Res.* 30(3):948–962.

Perin C, Vuillemot R, Stolper CD, Stasko JT, Wood J, Carpendale S (2018) State of the art of sports data visualization. *Comput. Graphics Forum* 37(3):663–686.

Plaisant C (2004) The challenge of information visualization evaluation. *Proc. Working Conf. Adv. Visual Interfaces*, 109–116.

Preim B, Lawonn K (2020) A survey of visual analytics for public health. *Comput. Graphics Forum* 39(1):543–580.

Rees D, Laramee RS (2019) A survey of information visualization books. *Comput. Graphics Forum* 38(1):610–646.

Roberts RC, Laramee RS (2018) Visualising business data: A survey. *Inform. (Basel)* 9(11):285.

Rouse WB (2015) *Modeling and Visualization of Complex Systems and Enterprises: Exploration of Physical, Human, Economic and Social Phenomena* (Wiley, Hoboken, NJ).

Ryan L (2016) *The Visual Imperative: Creating a Visual Culture of Data Discovery* (Morgan Kaufmann/Elsevier, Cambridge, MA).

Sackett P, Williams D (2003) Data visualization in manufacturing decision making. *J. Adv. Manufacturing Systems* 2(2):163–185.

Sampson SE (2012) Visualizing service operations. *J. Service Res.* 15 (2):182–198.

Shmueli G, Jank W, Aris A, Plaisant C, Shneiderman B (2006) Exploring auction databases through interactive visualization. *Decision Support Systems* 42(3):1521–1538.

Shu L, Jiang W, Tsui K (2008) Weighted CUSUM chart for detecting patterned mean shifts. *J. Quality Tech.* 40(2):194–213.

Singh SK, Jenamani M, Garg C, Alirajpurwala H (2019) Multi-echelon supply network analysis with interactive visualization. *Internat. Conf. Machine Learn. Big Data Cloud Parallel Comput.* (COMITCon), 481–484.

Singhal K, Feng Q, Ganeshan R, Sanders NR, Shanthikumar JG (2018) Introduction to the special issue on perspectives on big data. *Production Oper. Management* 27(9):1639–1641.

Sodhi MS, Tang CS (2014) Guiding the next generation of doctoral students in operations management. *Internat. J. Production Econom.* 150(C):28–36.

Stasko J (2014) Value-driven evaluation of visualizations. *Proc. 5th Workshop on Beyond Time and Errors: Novel Evaluation Methods for Visualization*, 46–53.

Sukchotrat T, Kim SB, Tsui K, Chen VCP (2011) Integration of classification algorithms and control chart techniques for monitoring multivariate processes. *J. Statist. Comput. Simulation* 81(12):1897–1911.

Sulek JM, Marucheck A, Lind MR (2006) Measuring performance in multi-stage service operations: An application of cause selecting control charts. *J. Oper. Management* 24(5):711–727.

Szafir DA (2018) The good, the bad, and the biased: Five ways visualizations can mislead (and how to fix them). *Interaction* 25(4):26–33.

Tarakci M, Ates N, Porck J, Vann Knippenberg D, Groenen P, de Haas M (2014) Strategic consensus mapping: A new method for testing and visualizing strategic consensus within and between teams. *Strategic Management J.* 35(7):1053–1069.

Tay L, Ng V, Malik A, Zhang J, Chae J, Ebert Y, Ding J, Zhao DS, Kern M (2018) Big data visualizations in organizational science. *Organ. Res. Methods* 21(3):660–688.

Thomas JJ, Cook KA (2005) *Illuminating the Path: The Research and Development Agenda for Visual Analytics* (National Visualization and Analytics Center).

Trier M (2008) Toward dynamic visualization for understanding evolution of digital communication networks. *Inform. Systems Res.* 19(3):335–350.

Tufte E (1983) *The Visual Display of Quantitative Information* (Graphics Press, Cheshire, CT).

Tufte E (2006) *Beautiful Evidence* (Graphics Press, Cheshire, CT).

Urabe Y, Yagi S, Tsuchikawa K, Masuda T (2019) Visualizing user action data to discover business process. *20th Asia-Pacific Network Oper. Management Sympos.*, 1–4.

Van de Ven AH (2007) *Engaged Scholarship: A Guide for Organizational and Social Research* (Oxford University Press, Oxford, UK).

Vliegen R, van Wijk JJ, van der Linden E (2006) Visualizing business data with generalized treemaps. *IEEE Trans. Visualization Comput. Graphics* 12(5):789–796.

Wall E, Agnihotri M, Matzen L, Divis K, Haass M, Endert A, Stasko J (2018) A heuristic approach to value-driven evaluation of visualizations. *IEEE Trans. Visualization Comput. Graphics* 25(1):491–500.

Wang K, Liang M, Li Y, Liu J, Liu RW (2019) Maritime traffic data visualization: A brief review. *IEEE 4th Internat. Conf. Big Data Analytics*, 67–72.

Ware C (2019) *Information Visualization: Perception for Design*, 4th ed. (Morgan Kaufmann/Elsevier, Cambridge, MA).

Zhang L, Stoffel A, Behrisch M, Mittelstadt S, Schreck T, Pompl R, Weber S, Last H, Keim D (2012) Visual analytics for the big data era—A comparative review of state-of-the-art commercial systems. *2012 IEEE Conf. Visual Analytics Sci. Tech. Proc.*, 173–182.

Zhang Y, Padman R, Patel N (2015) Paving the COWpath: Learning and visualizing clinical pathways from electronic health record data. *J. Biomedical Informatics* 58:186–197.

Zhu B, Watts SA (2010) Visualization of network concepts: The impact of working memory capacity differences. *Inform. Systems Res.* 21(2):327–344.