Visual Analytics: An early and continuing success of Convergent Research with impact

David S. Ebert
Data Science Institute for Societal Challenges (DISC Center), The University of Oklahoma

Audrey Reinert
Data Science Institute for Societal Challenges (DISC Center), The University of Oklahoma

Brian Fisher
School of Interactive Arts and Technology, Simon Fraser University

***Abstract*—The growth of the field of visual analytics reflects a sustained, long-term commitment to applying convergent research principles to computer science research. Charting the future research directions that the field of visual analytics will evolve towards requires an understanding of the field's rich, productive history of collaboration and a discussion of current challenges.**

Visual analytics has grown rapidly over the past two decades and has spread from a problem-driven convergent area of research at the intersection of visualization, human-computer interaction (HCI), data mining/analytics, statistics, decision science, and cognitive psychology to not only a large convergent research field, but also to deployed solutions and commercial products that are impactful and almost ubiquitous. From impactful, large commercial tools such as Tableau that is used by businesses, researchers, and universities across the globe, to ubiquitous, interactive visualization and analytics apps and websites on smartphones that citizens use every day, visual analytics has changed discovery, engineering, science, and decision making from everyday personal decision-making to global policy decision making, and its impact is still growing. VA's success can be attributed to two main factors: 1) its motivation and criteria for success was grand societal challenges; 2) its transdisciplinary teaming approach with commonly active engagement of the people who will use the solution. These factors ensure that large research challenges spanning multiple disciplines are tackled and that the real-world problems will benefit from core and applied research advances within visual analytics. This same approach is at the heart of convergence research that has recently gained acceptance as a new approach to impactful science [1] and also can be considered use-inspired research in

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Pasteur's Quadrant [2]. Attacking grand challenges with human engagement is great solution approach to *wicked problems* [3]and builds the stakeholder engagement that is needed to define a satisficing solution and gain consensus on actions to be taken [3].

BACKGROUND AND ORIGIN OF VISUAL ANALYTICS.

Visual analytics was defined in 2004 as "the science of analytical reasoning facilitated by interactive visual interfaces"[4]. The choice of terms in this definition placed the emphasis on reasoning and on a scientific approach to understanding how we reason and how it might be facilitated by interactive visual interfaces. In a general sense, all of computer graphics is dependent upon a scientific understanding of the capabilities of human vision. Whether it is a synthetic computer graphic environment or the graphical representation of abstract information, understanding how humans perceive and process visual stimuli in the world is foundational to graphics and visualization. Scientific visualization takes this a step further its emphasis on comprehensibility and utility in science.

Decisions about how best to represent and display a particular piece of information must be informed not only by the capabilities of the human visual system but also by an understanding of what aspects of those data are important and should be most salient and how the information ought to be displayed to support the kinds of reasoning that the user is likely to do. Because of this, scientific visualization designers maintain close contact with the scientific community, often including scientists in design processes and conducting extensive user testing.

Tackling other applications and types of data, information visualization expanded the human-computer collaboration with a focus on how visualization can be designed to support understanding the implications of many kinds of information by a broader and more diverse set of users [5]and how visual languages can be created that would present data in ways that were consistent across applications for easier understanding [6].This necessarily expanded the need for user research to better understand the perceptual and cognitive capabilities of this more diverse set of users, their motivations, goals and tasks.

While much of this research was presented in technical venues such as IEEE VIS, EuroVis, IEEE Transactions on Visualization and Computer Graphics, Information Visualization etc., other lines of inquiry used perceptual and cognitive science methods to devise and test theories of human perception and understanding of these graphical representations of information. Conferences on Diagrammatic Reasoning and the interdisciplinary Smart Graphics conferences helped to lay the groundwork for the cognitive science aspects of visual analytics.

A BRIEF HISTORY OF VISUAL ANALYTICS

The visual analytics approach to application development began with work at Pacific Northwest National Lab led by Dr. Pak Chung Wong on visual data mining [7], extending the ongoing work of Dr. Daniel Keim of the University of Konstance in tightly integrating visualization and data mining [4]. Pak introduced many of the ideas that form the core of the visual analytics approach, such as interaction design of human-information discourse and the role of the system in actively guiding the user through the analysis process to accurately and efficiently utilize the information for situation understanding and planning for actions to be taken [7]. These foundational principles of simplicity, user autonomy, reliability, reusability, availability, and security remain central to the visual analytics approach.

The work of Pak Wong and Jim Thomas in visual exploratory data analysis and mining inspired Dr. Joe Kielman to propose a large scale, U.S. government funded convergent research program to apply visual analytics techniques to analysis and decision making with disparate, confusing, and often conflicting data that homeland security personnel and first responders must face. In 2003, Jim Thomas devised a series of curated workshops of leading visualization, data analytics, data mining, cognitive psychology, and decision science researchers actively working with personnel from government agencies, industry, and first responder agencies to understand the challenges they face; the type, sources, and messiness of data streaming to their systems; their goals and challenges; and to then define a new field of science called visual analytics to solve these real-world challenges. To introduce the workshop, the following working definition was provided:

> "Visual Analytics is the formation of abstract visual metaphors in combination with a human information discourse (interaction) that enables *detection of the expected and discovery of the unexpected* within massive dynamically changing information spaces [8]. The goal of Visual Analytics is to stimulate deep analytical insight from massive, complex, and often conflicting information in order to yield an assessment having quantified certainty."

The output of these workshops was the definition, research agenda, first cohort of motivated researchers in visual analytics, and large-scale funded research networks in visual analytics in the United States, Canada, and Europe. The research agenda was published in book form as *Illuminating the Path, and R&D Agenda in Visual Analytics.* It defines visual analytics as "the science of analytical reasoning facilitated by interactive visual interfaces" [9], [10]. A key tenet of visual analytics is to provide actionable information and insights. Essential features for a visual analytics solution are the following:

- An interactive, integrated discovery/decision-making environment
- User-guided and perceptually-guided interface, interaction, and analysis
- A balance of human cognition and automated computerized analysis that amplifies human cognition and domain knowledge for more effective and efficient analysis, discovery, decision-making, and action
- Providing quantitative, reliable, understandable, reproducible information.

Not captured in the definition, but present in *Illuminating the Path*, was an emphasis on field studies of expert analysis in applications. This approach anticipated current efforts to better integrate basic and application-responsive research. In this way visual analytics anticipated the current HIBAR (Highly-Integrative Basic and Application Responsive) research approach. This integrative approach was further advanced to include AI and related approaches in the VISMASTER program definition of visual analytics as "Visual analytics combines automated analysis techniques with interactive visualizations for an effective understanding, reasoning and decision making on the basis of very large and complex datasets" [11].

Some classic early visual analytics systems using this HIBAR approach include the text and document VA systems Inspire [12] and Jigsaw [13], [14], spatial temporal VA systems such as LAHVA, PanViz, VALET, cgSARVA [15]–[20], SensePlace[21], GeoVista[22], CrimeViz[23], [24], and financial visual analytic systems such as PerformanceMatrix [25] and WireVis [26] that were developed in collaboration with domain experts to create effective tools solving real world problems.

One of the earliest and most widely used commercial successes of visual analytics is Tableau, which grew out of the Polaris project[27] at Stanford and evolved in parallel to the visual analytics field. Visual analytics information systems are now commonly used for business analytics and intelligence and the business community has helped grow and deploy visual analytics tools as the de facto method for analysis. Websites, such as the *New York Times* COVID-2 analysis and tracking pages are used daily by thousands of people, and even more people use visual analytic apps on their phones daily, with example such as the Fitbit app.

SPREAD TO OTHER DISCIPLINES

Early work in visual analytics found a place in IEEE Visualization and Graphics Technical Committee conferences, with the Visual Analytics Science and Technology (VAST) Symposium beginning at IEEE VIS 2006, becoming a full conference in 2010. This event sought to attract papers on basic scientific aspects of visual analytics and application of science in visualization and interaction design. The balance of the work presented at VAST and at EuroVA focused on application-responsive development. Research on the cognitive science aspects of visual analytics was slower to emerge. Early science-focused events were held in 2009 at the Annual Meeting of the Cognitive Science Society and in 2014 in the Annual Meeting of the Association for Psychological Science. An IEEE SMC Technical Committee "Visual Analytics and Communication" was established in 2015.

In more recent years, we have seen substantial growth in opportunities for publication and presentation of aspects of visual analytics that focus on perceptual and higher order cognition. VISxVision is a group that has been organizing symposia at both IEEE VIS and the Vision Sciences conference since 2019. VisPsych is a new group that seeks to bridge cognitive psychology and visualization by organizing associated events at conferences in both fields with extended proceedings to be published in book form. It is possible that these efforts to bridge the gap between application and science will finally enable researchers to "Create a science of visual representations based on cognitive and perceptual principles that can be deployed through engineered, reusable components" [2, pg7]. A more detailed overview of the field can be found in Cui[28].

In keeping with the initial focus on field studies of visually-enabled reasoning by expert analysts in their application domains, a substantial portion of visual analytics research can be found in application domains such as those found in the minitracks at HICSS, the Hawaii International Conference for Systems Sciences, data mining, business, health, geography, and AI conferences. These include a HICCS minitrack on visual analytics that has been offered in one form or another since 2009.

DIRECTIONS FOR FUTURE RESEARCH

The well-documented growth in the number of Visual Analytics research publications[28], [29], (See Figure 1) and commercial products is a positive indication of the continued growth of the field and its impact. While visual analytics has been quite successful, there are still great opportunities for improvement to achieve the goal of visual analysis to seamlessly increase the effectiveness and efficiency of human analysts in exploring issues and solving problems while harnessing the growth of digital data, the latest advances in analytical techniques, cognitive science, computing architectures, and artificial intelligence. Advances in these areas are needed to produce trustable, reproducible information from VA environments overall and not just in AI/ML-powered VA systems. These advances and evolution of VA will help drive convergent research in many related fields and further increase visual analytics' role in solving *wicked problems.* We highlight these opportunities below.

Data-enabled Reasoning

Enabling effective reasoning with a *variety* of data types and with data across scales, the *cross-scale problem,* still needs improved solutions incorporating natural scales [30], [30], [31]. and natural representations for abstract, fuzzy, data and concepts where humans have difficulty in effective reasoning, including risk, uncertainty, and time. New analytical techniques, perceptually-guided and cognitively-guided visualization techniques, and integrated visual environments are needed to increase the ease of human exploration, analyses, reasoning, and decision making with the variety of data available and needed for effective solutions. Enabling the exploration of the range of analytics results generated by data processing choices to ensure the best result, *multiverse analysis,* is an approach that also needs to be integrated into visual analytic environments [32].

Managing Bias

Enabling decision-making environments where data and human bias are transparent and efficiently managed is a growing challenge as more decision-making is data-driven. VA environments must take into account bias in data distributions, conscious and unconscious bias of the user and reveal these to the user so that the bias can be effectively managed and improved results and decisions are the outcome. These issues are present in most VA environments and often remain unaddressed. The

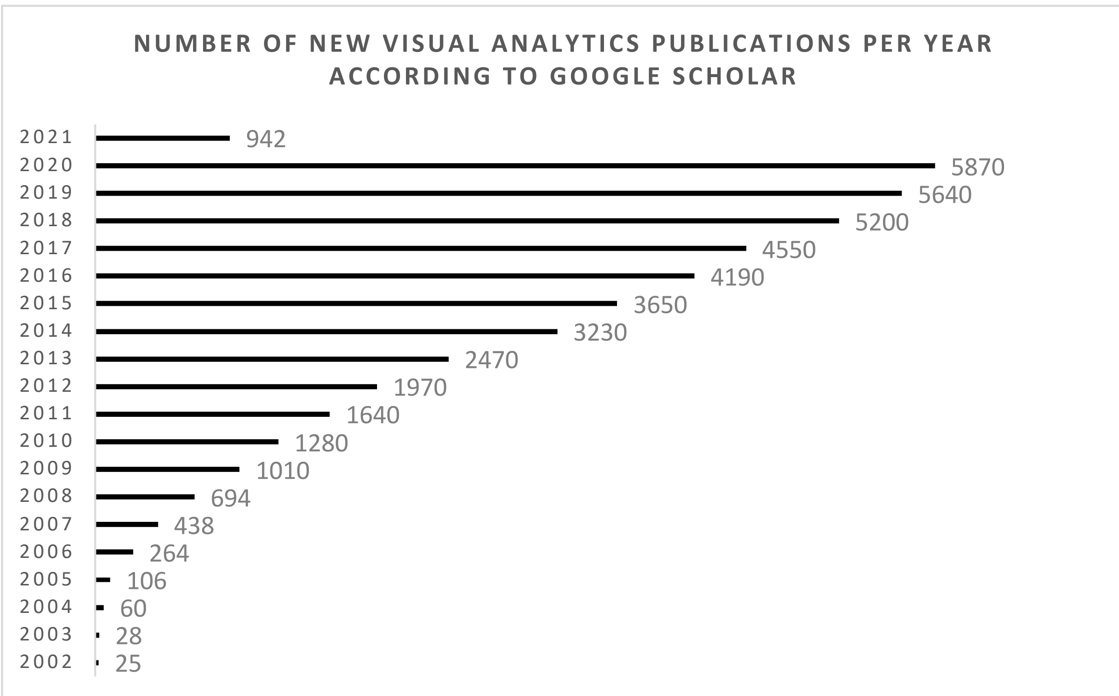

Figure 1 Chart of the number of New Visual Analytics Publications per year as indexed by Google Scholar as of March 14th, 2021

problem is even more severe with complex, opaque data processing and analytics such as machine learning. Fortunately, this is a burgeoning area of research in the VA community (e.g.,[33]) and as it grows, these techniques and solutions should be integrated into all VA systems.

Seamless integration of human analysis and computer analysis in the form of a Human-Computer collaboration and teaming for effective exploration, analysis, discovery and decision, or as Licklider called it a true Man-Computer Symbiosis[34] .

Trustable, Understandable Machine Learning

A benefit of using AI-enabled decision support systems is that humans can offload the execution of complex, multi-stage calculations or other rote, repetitive tasks to focus on making judgements and decisions. This benefit arises from the fact that AI systems consume, process, analyze and interpret large volumes of data with greater speed and precision than humans. This allocation of labor between the members of the human-AI team increases the analytical capabilities and effectiveness of the human- computer team while partially addressing the challenges of scalability and evaluation.

However, introducing AI into the decision-making process creates complications. As AI systems become increasingly complex, the understandability of the underlying mechanisms used to arrive at conclusions become opaque and difficult for humans to understand. This opaqueness leads individuals to discount or distrust the recommendations of AI systems [35], [36].

One solution to this complexity problem that visual analytics can provide centers on providing a clear, understandable explanation of how an AI arrives at the presented information. While a user may not need to know which cluster of neurons in a 500,000-neuron network are responsible for the result, they do need to understand what information contributed to the result and how it makes sense for the situation at hand. Human-Centered AI techniques allow humans to better understand, trust, and manage how an AI system arrive at a conclusion while turning AI's from black boxes to glass boxes [37], [38].

Investments in trustable and understandable development will positively benefit visual analytics research in the coming years as well as lead to more rapid deployment of trustable AI solutions for complex problems. From a user experience perspective, understandable systems would demystify how a solution was reached and partially correct public misperceptions around AI. Critically, such systems will enable trustable, AI-enhanced visual analytics to address questions of bias in the analytics process. An understandable AI-based solution with user-understandable, explorable explanations how it arrived at the results, point to the data it used to learn associations, and illustrate the learning process in simple terms will illuminate how biases in the data collection, ingestion, and analysis processes influence the outcome. This transparency and understandability of an interactive visual environment are critical for dependable, trustable solutions.

Human-guided, Interactive Machine Learning

A limitation of the techniques discussed above is that

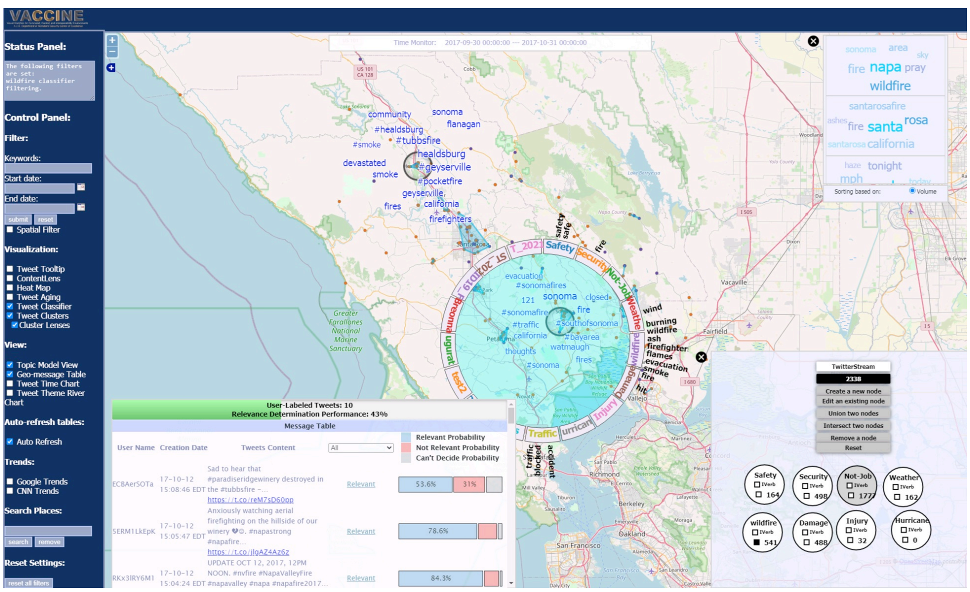

Figure 2: Example of a Human Guided Interactive Machine Learning System title SMART from [46].

inherently they place the user in a passive role in much of the analysis and do not harness the user's expertise, domain knowledge, and knowledge that is not in digital form. What if the user was given the tools to influence which subset of data a system prioritized, incorporated their skills, knowledge, and expertise? The user can bring guidance that can include their understanding of ethical and governance aspects, as well as the pragmatics of the situation and provenance of the data.

One technique to accomplish this is through inclusion of interactive, human-guided machine learning into the model training and evaluation process. Human-guided interactive machine learning (HGIML) empowers a user to train a model and modify the resulting solution in near real-time [39], [40] by selecting specific features for inclusion or exclusion, as well as guide the analytical process over time. HGIML systems is especially beneficial in synthesizing and analyzing ambiguous data. IML is one form of mixed-initiative analytics [41]–[43] where the human steers the analytical process during the human-computer exploration and analysis process. One technique to accomplish this is through inclusion of interactive machine learning into the model building and evaluation process. Interactive machine learning empowers a user to train a model and modify the resulting solution in near real-time [39], [40] by selecting specific features for inclusion or exclusion. IML systems will be especially beneficial in synthesizing and analyzing ambiguous data. Another method, termed mixed initiative [41]–[43], would place the human in a more active role by enabling the steer the direction the analytical system went.

For example, analyzing social media data to detect and correct for misinformation has become an important challenge [44], [45]. However, applying a purely keyword-based filter to classify social media data can lead to erroneous classifications and possible misclassification of text strings.

An HGIML classifier would present a user with a subset of the incoming data that contained certain predefined keywords or hashtags [46] (See **Error! Reference source not found.**). The user would then label the data as relevant or irrelevant based on their subjective opinion.

An advantage of using human-guided, interactive machine learning is the creation of more direct engagement in thinking about the data and analytics processes together with a sense of agency in the user, empowering them to make decisions about data relevancy. The added benefit of enhanced user agency is an increase in the overall trust in the final solution, increasing stakeholder-buy-in and solution acceptance. Further, HGIML addresses a scalability problem by focusing the user's attention on high level analysis while permitting them to drill down to specific items of interest. This reduction in task complexity benefits the user by allowing them to accomplish a simpler, more understandable task, diving deeper into analytic processes as needed.

However, a challenge facing the visual analytics community when implementing interactive machine learning is the need for intuitive, natural interactions. The solution to the challenge is dependent upon the type of task the user is being asked to complete. A binary classification task – i.e., relevant or not relevant- would require fewer inputs than a complex choice.

Naturalistic Human-Computer Collaborative Exploration and Decision-Making Environments

Science fiction and other aspects of popular culture present images of seamlessly interconnected computing technologies that augment human capabilities when solving complex problems. The reality is more complicated. Designing such a fluid system of seamless interactions requires understanding how to develop smooth, seamless, and powerful interactions; investments in responsive, interactive and rapidly updated graphics; and careful, conscientious, and comprehensive understanding of user experiences [47]. These tools need to effectively leverage mathematical models, AI and ML, visualization, and human intuition while adjusting for the changing needs and priorities of the user. Semantic interaction techniques[48] do provide one such solution some applications.

The rapid increase in the volume and rate at which systems generate, collect, and store data pose serious challenges to effective human-computer collaborative decision-making environments. Human perceptual and cognitive capabilities cannot make sense of large volumes of data without some form of transformation and reduction within perception limits. Further, human analytical capabilities become overwhelmed when presented with hundreds of possible options to compare. Thus, if not provided with the necessary tools to effectively sort, filter, synthesize, and navigate this sea of data, humans turn to sub-optimal heuristics to assist them making a decision.

One of the challenges facing the visual analytics research community is the need to provide users with intuitive tools needed to transform this data deluge into navigable, understandable information that can be analyzed, explored, synthesized and utilized for trustable, reproducible decision making and discovery. This challenge can in part be addressed by empowering the user through fluid, natural, and simple interactions with tractable amounts of information. Both Trustable, Understandable AI and Human-Guided Interactive Machine Learning aid in this empowerment by reframing complex tasks in simple, easily understandable terms. While humans may not be skilled at processing and discerning patterns from large volumes of data, they are skilled at making decisions and classifications. Asking a user to make a choice about what data to include or exclude and showing them the consequence of their choice does not require special training.

Furthermore, seamless integration of human analysis and computer analysis in the form of a Human-Computer Collaboration and teaming for effective exploration, analysis, discovery and decision, or as Licklider called it a true *Man-Computer Symbiosis*[34] .This symbiosis that leverages the expertise, knowledge, and skills of the human with the data processing and analysis of the computerized algorithms has been the goal of visual analytics since its inception.

CONCLUSION

Visual analytics coalesced as a field in 2004 with the belief that the design and testing of highly interactive visualization environments could greatly benefit from a companion science of analytical reasoning in interactive visualization environments, incorporating convergent expertise in statistics and decision-science, cognitive and perceptual psychology, human-computer interaction, and visualization. The objectives of this new science emerged from studies of real-world analytic practices and technologies, ensuring that scientific theories and findings could be used to create visualization environments that provably support effective human reasoning in solving everyday tasks to societal challenges. The result has been improved analysis, planning, problem-solving, and operational management in a broad range of applications that require human reasoning and judgement.

In the intervening years, substantial progress has been made in adapting, modifying, and applying perceptual and cognitive science research to the design and testing of interactive visualization interfaces. This has made science-aware design and testing of interactive visualization systems accessible to a much larger proportion of the engineering community. The resulting engagement of the engineering community with these efforts has begun to attract the attention of scientific researchers, supporting VISxVision and VisPsych in their efforts to bring new application-responsive research questions to attention of the broader cognitive science community. If successful, the resulting “virtuous cycle” will help to better coordinate basic and application-responsive research, resulting in both better science and more effective application of interactive visualization, discovery, and analysis environments in a broad range of applications, from every-day decisions to grand challenges. The challenges that must now be addressed are to consolidate the gains that have been made in interdisciplinary VA research and to reach out to new application communities to ensure that visual analytics research helps to achieve the goal of IEEE of “advancing technology for the benefit of humanity”

■ REFERENCES

[1] N. R. Council and others, *Convergence: Facilitating transdisciplinary integration of life sciences, physical sciences, engineering, and beyond*. National Academies Press, 2014.

[2] D. E. Stokes, *Pasteur’s quadrant: Basic science and technological innovation*. Brookings Institution Press, 2011.

[3] H. W. Rittel and M. M. Webber, “Dilemmas in a general theory of planning,” *Policy sciences*, vol. 4, no. 2, pp. 155–169, 1973.

[4] D. A. Keim, “Visual data mining,” 1997.

[5] J. Bertin, “Semiology of graphics; diagrams networks maps,” 1983.

[6] L. Wilkinson, “The grammar of graphics. 690 p,” *Springer-Verlag, New York, USA*, vol. 37, pp. 1975–1982, 2005.

[7] P. C. Wong, “Visual data mining,” *IEEE Computer Graphics and Applications*, vol. 19, no. 5, pp. 20–21, 1999.

[8] Pak Chung Wong and J. Thomas, “Visual Analytics,” *IEEE Comput. Grap. Appl.*, vol. 24, no. 5, pp. 20–21, Sep. 2004, doi: 10.1109/MCG.2004.39.

[9] K. A. Cook and J. J. Thomas, “Illuminating the path: The research and development agenda for visual analytics,” Pacific Northwest National Lab.(PNNL), Richland, WA (United States), 2005.

[10] J. J. Thomas and K. A. Cook, “A Visual Analytics Agenda,” *IEEE Comput. Graph. Appl.*, vol. 26, no. 1, pp. 10–13, Jan. 2006, doi: 10.1109/MCG.2006.5.

[11] “Chapter 2 – Visual Analytics - VisMaster.” https://www.vismaster.eu/book/chapter-2-visual-analytics/ (accessed Mar. 14, 2021).

[12] K. A. Papanikolaou, M. Grigoriadou, H. Kornilakis, and G. D. Magoulas, “Personalizing the Interaction in a Web-based Educational Hypermedia System: the case of INSPIRE,” *User modeling and user-adapted interaction*, vol. 13, no. 3, pp. 213–267, 2003.

[13] C. Gorg, Z. Liu, N. Parekh, K. Singhal, and J. Stasko, “Visual analytics with Jigsaw,” in *2007 IEEE Symposium on Visual Analytics Science and Technology*, 2007, pp. 201–202.

[14] J. Stasko, C. Görg, and Z. Liu, “Jigsaw: supporting investigative analysis through interactive visualization,” *Information visualization*, vol. 7, no. 2, pp. 118–132, 2008.

[15] R. Maciejewski *et al.*, “Lahva: Linked animal-human health visual analytics,” in *2007 IEEE Symposium on Visual Analytics Science and Technology*, 2007, pp. 27–34.

[16] L. Snyder, A. Reinert, and D. Ebert, “PanViz 2.0: Intregating AI into Visual analytics to adapt to the novel

challenges of COVID-19," in *Proceedings of the 54th Hawaii International Conference on System Sciences*, 2021, p. 1457.
[17] A. Reinert *et al.*, "Visual Analytics for Decision-Making During Pandemics," *Computing in Science & Engineering*, vol. 22, no. 6, pp. 48–59, 2020.
[18] M. Karimzadeh, J. Zhao, G. Wang, L. S. Snyder, and D. S. Ebert, "Human-guided visual analytics for big data.," 2020.
[19] A. Malik, R. Maciejewski, T. F. Collins, and D. S. Ebert, "Visual analytics law enforcement toolkit," in *2010 IEEE International Conference on Technologies for Homeland Security (HST)*, 2010, pp. 222–228.
[20] T. Kapler and W. Wright, "GeoTime Information Visualization," *Information Visualization*, vol. 4, no. 2, pp. 136–146, Jun. 2005, doi: 10.1057/palgrave.ivs.9500097.
[21] A. M. MacEachren *et al.*, "Senseplace2: Geotwitter analytics support for situational awareness," in *2011 IEEE conference on visual analytics science and technology (VAST)*, 2011, pp. 181–190.
[22] A. C. Robinson, J. Chen, E. J. Lengerich, H. G. Meyer, and A. M. MacEachren, "Combining usability techniques to design geovisualization tools for epidemiology," *Cartography and Geographic Information Science*, vol. 32, no. 4, pp. 243–255, 2005.
[23] R. E. Roth, K. S. Ross, B. G. Finch, W. Luo, and A. M. MacEachren, "A user-centered approach for designing and developing spatiotemporal crime analysis tools," in *Proceedings of GIScience*, 2010, vol. 15.
[24] R. E. Roth, K. S. Ross, and A. M. MacEachren, "User-centered design for interactive maps: A case study in crime analysis," *ISPRS International Journal of Geo-Information*, vol. 4, no. 1, pp. 262–301, 2015.
[25] H. Ziegler, T. Nietzschmann, and D. A. Keim, "Visual Analytics on the Financial Market: Pixel-based Analysis and Comparison of Long-Term Investments," in *2008 12th International Conference Information Visualisation*, London, UK, Jul. 2008, pp. 287–295, doi: 10.1109/IV.2008.80.
[26] R. Chang *et al.*, "Wirevis: Visualization of categorical, time-varying data from financial transactions," in *2007 IEEE Symposium on Visual Analytics Science and Technology*, 2007, pp. 155–162.
[27] C. Stolte, D. Tang, and P. Hanrahan, "Polaris: A system for query, analysis, and visualization of multidimensional relational databases," *IEEE Transactions on Visualization and Computer Graphics*, vol. 8, no. 1, pp. 52–65, 2002.
[28] W. Cui, "Visual analytics: A comprehensive overview," *IEEE Access*, vol. 7, pp. 81555–81573, 2019.
[29] I. J. Akpan and A. A. Akpan, "Multiple criteria analysis of the popularity and growth of research and practice of visual analytics, and a forecast of the future trajectory," *International Transactions in Operational Research*, 2021.
[30] A. Malik, R. Maciejewski, S. Towers, S. McCullough, and D. S. Ebert, "Proactive spatiotemporal resource allocation and predictive visual analytics for community policing and law enforcement," *IEEE transactions on visualization and computer graphics*, vol. 20, no. 12, pp. 1863–1872, 2014.
[31] R. L. Habeeb, J. Trebilco, S. Wotherspoon, and C. R. Johnson, "Determining natural scales of ecological systems," *Ecological Monographs*, vol. 75, no. 4, pp. 467–487, 2005.
[32] Y. Liu, A. Kale, T. Althoff, and J. Heer, "Boba: Authoring and visualizing multiverse analyses," *IEEE Transactions on Visualization and Computer Graphics*, 2020.
[33] E. Wall, J. Stasko, and A. Endert, "Toward a Design Space for Mitigating Cognitive Bias in Vis," in *2019 IEEE Visualization Conference (VIS)*, 2019, pp. 111–115.
[34] J. C. Licklider, "Man-computer symbiosis," *IRE transactions on human factors in electronics*, no. 1, pp. 4–11, 1960.
[35] M. Körber, E. Baseler, and K. Bengler, "Introduction matters: Manipulating trust in automation and reliance in automated driving," *Applied ergonomics*, vol. 66, pp. 18–31, 2018.
[36] H. A. Abbass, "Social integration of artificial intelligence: functions, automation allocation logic and human-autonomy trust," *Cognitive Computation*, vol. 11, no. 2, pp. 159–171, 2019.
[37] A. Rai, "Explainable AI: From black box to glass box," *Journal of the Academy of Marketing Science*, vol. 48, no. 1, pp. 137–141, 2020.
[38] D. Gunning, "Explainable artificial intelligence (xai)," *Defense Advanced Research Projects Agency (DARPA), nd Web*, vol. 2, p. 2, 2017.
[39] J. A. Fails and D. R. Olsen Jr, "Interactive machine learning," in *Proceedings of the 8th international conference on Intelligent user interfaces*, 2003, pp. 39–45.
[40] S. Amershi, M. Cakmak, W. B. Knox, and T. Kulesza, "Power to the people: The role of humans in interactive machine learning," *Ai Magazine*, vol. 35, no. 4, pp. 105–120, 2014.
[41] K. Cook *et al.*, "Mixed-initiative visual analytics using task-driven recommendations," in *2015 IEEE Conference on Visual Analytics Science and Technology (VAST)*, Chicago, IL, USA, Oct. 2015, pp. 9–16, doi: 10.1109/VAST.2015.7347625.
[42] E. Wall, S. Das, R. Chawla, B. Kalidindi, E. T. Brown, and A. Endert, "Podium: Ranking data using mixed-initiative visual analytics," *IEEE transactions on visualization and computer graphics*, vol. 24, no. 1, pp. 288–297, 2017.
[43] A. Coscia, D. H. Chau, and A. Endert, "Toward a Bias-Aware Future for Mixed-Initiative Visual Analytics," *arXiv preprint arXiv:2011.09988*, 2020.
[44] M. Canan and D. Canan, "Countering Disinformation Propaganda: Reverse Engineering the Experimental Implicit Learning Paradigm," in *ICCWS 2020 15th International Conference on Cyber Warfare and Security*, 2020, p. 92.
[45] C. VanDam, *Learning Algorithms for Detecting Disinformation on Social Media*. Michigan State University, 2019.
[46] L. S. Snyder, Y.-S. Lin, M. Karimzadeh, D. Goldwasser, and D. S. Ebert, "Interactive Learning for Identifying Relevant Tweets to Support Real-time Situational Awareness," *IEEE Trans. Visual. Comput. Graphics*, pp. 1–1, 2019, doi: 10.1109/TVCG.2019.2934614.
[47] N. Elmqvist, A. V. Moere, H.-C. Jetter, D. Cernea, H. Reiterer, and T. Jankun-Kelly, "Fluid interaction for information visualization," *Information Visualization*, vol. 10, no. 4, pp. 327–340, 2011.
[48] A. Endert, P. Fiaux, and C. North, "Semantic interaction for visual text analytics," in *Proceedings of the 2012 ACM annual conference on Human Factors in Computing Systems - CHI '12*, Austin, Texas, USA, 2012, p. 473, doi: 10.1145/2207676.2207741.

David S. Ebert is an Associate Vice President for Research and Partnerships, the Gallogly Chair Professor of Electrical and Computer Engineering, and Director of the Data Institute for Societal Challenges at the University of Oklahoma. He is an IEEE Fellow, recipient of the 2017 IEEE Computer Society VGTC Technical Achievement Award, member of the IEEE VGTC Visualization Academy, an adjunct Professor of Electrical and Computer Engineering at Purdue University, and Director of the Visual Analytics for Command Control and Interoperability Center (VACCINE), the Visualization Science team of the Department of Homeland Security's Visual Analytics and Data Analytics Emeritus Center of Excellence. Dr. Ebert received his Ph.D. in Computer and Information Science from The Ohio State University and performs research in visual analytics, novel visualization techniques, interactive machine learning and explainable AI, human-computer teaming, advanced predictive analytics, and procedural abstraction of complex, massive data.

Audrey Reinert is a Postdoctoral Researcher at the University of Oklahoma's Data Science Institute for Societal Challenges (DISC Center). She holds a PhD in Industrial Engineering from Purdue University (2019), a Masters in Human Computer Interaction from the Georgia Institute of technology (2015), and a Bachelors in Cognitive Neuropsychology from the University of California, San Diego (2012). Her research interests lie at the intersection of human centered computing, data visualization, and human machine interaction. She is a member of IEEE, HFES, and the AGU and can be reached at areinert@ou.edu

Brian Fisher is a Professor in the School of Interactive Arts and Technology at Simon Fraser University. He is International Liaison Chair of the IEEE VGTC, a Fellow of the Psychonomics Society, and member of the DRDC Institute for Research in Defence and Security Centre of Expertise on Human System Performance and the EUREKA / European Commission Eurostars Independent Expert Panel. Fisher received his Ph.D. in Cognitive Psychology from the University of California. His Integrated Science Lab combines scientific investigation of human reasoning with graphical information systems and cognitive engineering of those systems for information understanding, analysis, and collaboration. Prior to SFU, Brian was an adjunct professor in Social Sciences (psychology), Commerce (entrepreneurship & MIS), and Science (Computer Science) as well as the Associate Director of the Media And Graphics Interdisciplinary Centre (MAGIC).