Engage, Explore, Enlighten: Proposing an Interactive Visualization and Analysis Model (IVAm) in Quantitative Research

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ABSTRACT

The landscape of quantitative research is getting transformed by increasing complexity of data as well as growing demand for knowledge that is accessible. Users often find it hard to engage with traditional methods used in analyzing and presenting data thus giving shallow insights. IVAm is a new concept that calls for the integration of dynamic data visualization techniques to promote better interpretation, accessibility, and engagement with data. IVAm is not just about having tools; it advocates for a comprehensive approach that nurtures user-centric interaction, encourages transparency, and enables different audiences to use data so as to make informed decisions. The paper discusses the theoretical underpinnings, key principles, and methodological framework behind IVAm which can revolutionize how data are presented, enhance understanding and increase the reach of quantitative research. Lastly, it highlights some of the challenges faced by this approach as well as its future directions thereby setting grounds for further development and application of IVAm.

INTRODUCTION

The Interactive Visualization And Analysis Model (IVAm) emerges as a beacon of innovation in the landscape of quantitative research, a transformation necessitated by the relentless march towards digital technologies. This paradigm shift is not merely a technical evolution; it is a profound rethinking of how we engage with data and knowledge. As Maulana et al. (2019) insightfully observe, digital technology has revolutionized the very nature of quantitative research by producing data that resonates with users' needs, thereby reshaping the research landscape. This digital renaissance has also permeated qualitative research, introducing tools like qualitative data analysis software (QDAS) and the Internet, which, while empowering, have ushered in a new set of ethical considerations, including researcher preparation and post-research responsibilities (Davidson et al., 2016). Furthermore, the advent of digital technologies has unlocked novel approaches to data collection and analysis, championing computer software-based quantitative inquiry that leverages software programs for insightful analyses (Cope, 2014).

In today's digital era, the traditional, static presentation of information is rapidly becoming obsolete. The demand for methods that not only efficiently convey complex information but also captivate a diverse audience is at an all-time high. This necessity stems from the digital realm's capacity to transform qualitative data into quantitative insights, enabling multimodal text analyses grounded in integrated theoretical frameworks and empirically validated tools (O'Halloran et al., 2018). Tiwasing et al. (2023) highlight the profound impact of digital technologies across various domains, including entrepreneurship research, where access to information, data, and analytical tools has been dramatically enhanced. The financial sector, too, has witnessed a metamorphosis with the advent of digitization, giving rise to novel business models and research opportunities (Gomber et al., 2017). In the educational sphere, a generational divide is evident in the adoption of digital learning materials, with younger teachers more readily embracing these innovations compared to their older counterparts (Camilleri & Camilleri, 2017). Moreover, the digital capabilities of SMEs are shaping new market offerings and processes, underscoring the pivotal role of human, technical, and innovation capabilities in the digital age (Nasiri et al., 2020).

Within this context, IVAm stands as a testament to the transformative power of digital technologies in reshaping educational research. The model's emphasis on engagement, exploration, and enlightenment aligns seamlessly with the objectives of educational research, fostering a more interactive, inquiry-based, and enlightening learning experience. Engaging learners and researchers in the process of data exploration and analysis is a fundamental goal in educational research. The exploration component of IVAm underscores the importance of discovery and inquiry in educational research methodologies. It advocates for a learning process rooted in interactive exploration of data, a method that has been shown to enhance learning outcomes. Enlightening learners and researchers is another critical dimension of IVAm. It suggests that the model is instrumental in facilitating understanding and knowledge acquisition, a primary goal in educational research. This enlightening role of IVAm is evident in the way digital technologies have influenced various sectors, including the financial industry, which has seen the emergence of new business models and opportunities.

The Interactive Visualization And Analysis Model (IVAm) is not just a tool but a harbinger of a new era in educational research, where engagement, exploration, and enlightenment are not mere buzzwords but the very pillars of a transformative educational experience. As we navigate this digital age, IVAm stands as a beacon, guiding us towards a future where data is not just analyzed but experienced, where learning is not just acquired but discovered, and where knowledge is not just imparted but enlightened.

NEED FOR CHANGE

The need for change in quantitative research is underscored by the limitations of current practices, including static data presentation, inadequate user interaction, and accessibility concerns. These limitations have been increasingly recognized in the context of the evolving digital landscape, prompting a shift towards more dynamic and interactive research methodologies.

- **Limitations of Current Practices**

Traditional methods in quantitative research often rely on static forms of data presentation, such as charts and graphs. These methods can be limiting in conveying the full scope and depth of the data, potentially obscuring complex relationships within the data. Static data presentation can fail to engage the audience effectively, leading to a superficial understanding of the research findings (Tran, 2019). The static nature of these presentations does not adequately cater to the dynamic and interconnected nature of modern data sets. Current practices in quantitative research often do not allow for meaningful interaction with the data. This lack of interactivity can hinder the audience's understanding and engagement, making it difficult for them to draw insights from the data (Ross & Zaidi, 2019). The absence of interactive elements in data presentation restricts the audience's ability to explore and manipulate the data, thereby limiting their capacity to engage in deeper analysis and understanding.

Traditional methods of data presentation in quantitative research can be inaccessible to those without specialized training, limiting the reach and impact of research findings. This creates a barrier to wider understanding and application of research insights, particularly for non-expert audiences (Hurst et al., 2011). The inaccessibility of traditional quantitative methods restricts the democratization of data and knowledge, hindering the potential for broader societal impact.

- **Evolving Research Demands**

The digital advancements and global trends towards transparency and accessibility have reshaped research design and presentation. The progression of digital technology and the movement towards open research emphasize the need for innovative approaches like IVAm. The advancement of digital technology has transformed expectations around data presentation in quantitative research. Interactive and dynamic methods are increasingly seen as essential for effective communication of research findings. Digital technologies have led to new forms of flexible work, such as crowdwork, highlighting the need for transparency in platform architecture, design, and algorithms (Rani & Furrer, 2020). Additionally, digital technology supports methods in data science, task sharing, and early intervention, especially in lower-resource settings, emphasizing the importance of adaptable and accessible digital tools in research (Naslund et al., 2019). These advancements necessitate a shift from traditional static methods to more dynamic and interactive approaches in quantitative research.

There is a global movement towards greater transparency and accessibility in research. This trend underscores the need for methodologies like IVAm, which promote openness and inclusivity in the presentation of research findings. Digital technologies have increased organizational transparency, requiring new forms of control and employee engagement (Gierlich-Joas, Hess, & Neuburger, 2020). The digital society demands greater institutional and political transparency, influenced by the openness and accessibility characteristics of the Internet (Díez-Garrido, 2017). Digital Humanities (DH) research has started to change this tradition by focusing on research accessibility, transparency, and dissemination, encouraging replicability (Viola, 2020). Digitalization in agriculture, for example, leads to data becoming a resource, enhancing traceability and transparency, but also posing privacy risks and challenging farmers' market positions (Linsner et al., 2021). Similarly, digitalization in disaster relief operations in Pakistan creates transparency and builds trust, benefiting society and disaster victims (Iqbal & Ahmad, 2022). These examples illustrate the global trend towards using digital technologies to enhance transparency and accessibility in various fields, including research.

CONCEPTUALIZING IVAm

IVAm is a paradigmatic shift in data interpretation and presentation, rooted in a distinct philosophical foundation and guided by key principles. This model represents a comprehensive approach that integrates interactive, dynamic, and user-centered methodologies, significantly enhancing the way data is analyzed and communicated.

- **Conceptual Framework**

IVAm is grounded in the philosophy of interactive, dynamic, and user-centered data interpretation and presentation. This philosophy is aligned with the Interactive Qualitative Analysis method, which emphasizes a systems approach to qualitative research, integrating elements of co-creation and service systems (Sandelowski, 2005; Makkonen & Olkkonen, 2017). The core idea is to shift from a passive consumption of information to an active engagement with data, enabling users to interact with and manipulate data in real-time. This approach not only enhances the understanding of complex datasets but also fosters a more inclusive and participatory research environment. The interactive and dynamic nature of IVAm aligns with contemporary digital advancements, where data is not static but constantly evolving. By adopting this philosophy, IVAm addresses the need for methodologies that can adapt to and reflect the dynamic nature of data in the digital age. This approach is particularly relevant in fields where data is complex and multifaceted, requiring a nuanced and flexible method of analysis and presentation.

IVAm is guided by principles that emphasize clarity, accessibility, user engagement, and ethical data use. These principles ensure that data visualizations are not only informative but also engaging and easy to understand for a broad audience (Angelini et al., 2020; Cleveland & McGill, 1984). Clarity in IVAm involves presenting data in a manner that is easily comprehensible, avoiding unnecessary complexity and focusing on conveying the essential aspects of the data. Accessibility is about making data understandable to people with varying levels of expertise, including those without specialized training in data analysis. User engagement in IVAm is about creating visualizations that are interactive and engaging, encouraging users to explore and interact with the data. This aspect is crucial for fostering a deeper understanding and facilitating a more active role for users in the research process. Ethical data use is another fundamental principle of IVAm, ensuring that data is used responsibly, respecting privacy and confidentiality, and presenting data in a manner that is truthful and transparent.

These guiding principles of IVAm contribute to creating a research environment that is not only effective in terms of data analysis and presentation but also ethical, inclusive, and user-friendly. By adhering to these principles, IVAm facilitates a more comprehensive and engaging approach to quantitative research, enhancing the overall quality and impact of research findings.

- **Methodological Framework**

IVAm integrates several core components that collectively enhance the process of data visualization and analysis. These components include dynamic data visualization, enhanced data interpretation, accessibility and engagement, educational and collaborative value, and tool agnosticism. Each of these elements plays a crucial role in making IVAm an effective and versatile tool for modern research. IVAm emphasizes the use of interactive and dynamic visualization tools, crucial for meaningful engagement with data. Dynamic visualization enables users to interact with and manipulate data in real-time, offering a more immersive and insightful experience. Recent advancements in visualization tools have further enhanced this capability, making it possible to transform static data into engaging, interactive experiences (Bajaj, 1997; Jing, Li, & Hu, 2017). A study by Chmielewski et al. (2019) explores the application of augmented reality, mobile devices, and sensors for quantitative assessment in combat scenarios, demonstrating the potential of dynamic visualization in decision-making and situational awareness.

The model facilitates deeper insights into complex datasets, enabling researchers to uncover hidden patterns and relationships. This enhanced data interpretation is crucial for accurate and comprehensive research findings, as it allows for a more detailed and sophisticated analysis of data. The integration of advanced analytical tools in IVAm supports methodologies that enable a more nuanced understanding of data, contributing to more informed decision-making and research conclusions (Palha, 2017; Bach, 2016). Ayad et al. (2019) discuss quantitative metrics for mutation testing, highlighting the importance of enhanced data interpretation in software technologies. IVAm makes quantitative data more accessible and engaging to a broader audience, including those without extensive technical expertise. This democratization of data understanding is crucial in making research findings more relatable and easier to comprehend for non-experts. The model's focus on accessibility ensures that research findings are communicated in a manner that is understandable and engaging to a wide range of audiences (Isenberg et al., 2011; Johansson & Jern, 2007). Jia et al. (2019) conducted a large-scale bibliometric analysis on sustainability research in business and management, illustrating how visualization can enhance accessibility and engagement in research.

IVAm serves educational purposes and fosters a collaborative environment. In educational settings, it can be used as a tool to teach complex concepts interactively and engagingly. It also promotes collaboration among researchers, educators, and students, encouraging a more participatory approach to learning and research. The model's emphasis on collaboration and education enhances its utility in academic and research settings (Jern, 2008; Lundblad & Jern, 2013). Wan et al. (2019) discuss the potential of light-sheet microscopy for understanding developmental processes, reflecting the educational and collaborative value of advanced visualization techniques. A key aspect of IVAm is its flexibility and adaptability to various research contexts and technologies. This tool agnosticism means that IVAm is not tied to any specific software or technology, allowing it to be used across different platforms and tools. This flexibility is crucial in a rapidly evolving digital landscape, where new technologies and tools are constantly emerging. IVAm's adaptability ensures that it remains relevant and effective, regardless of the specific tools or technologies used in research. Gicheru and Kariuki (2019) examined the influence of dynamic capabilities on the performance of commercial banks in Kenya, indicating the adaptability of dynamic tools in different research contexts.

THEORETICAL FRAMEWORK VALIDATION

By aligning itself with existing theoretical frameworks, IVAm strengthens its credibility and demonstrates its potential for wide adoption across various research disciplines. This potential is backed up by theoretical framework validation that aligns IVAm with established theories from cognitive psychology, human-computer interaction, and communication studies. The theoretical framework validation of IVAm is important because it strengthens its credibility and demonstrates that it has the potential to be widely adopted in different research areas.

IVAm's principles and methods are rooted in well-known theories which provide strong evidence supporting the effectiveness of the model. For example, Sedig and Parsons (2013) presents a paper which supports complex cognitive activities using visualization-based computational tools – something relevant to IVAm's focus on human-information interaction in complex cognitive activities (Sedig & Parsons, 2013). Furthermore, Parsons and Sedig (2014) discuss the modifiability of visual representations as they relate to enhancing coordination between humans and artifacts – this fits into what IVAm seeks to achieve (Parsons & Sedig, 2014).

Further support for the theory base comes from the work by Meyer and Kieras (1997) where they examine goodness of fit of EPIC model with regard to executive cognitive processes as well multiple task performance. This research is supportive of what IVAm stands for because it promotes user engagement through attentional principles such as motivation or feedback given during action execution (Meyer & Kieras, 1997). Similarly, Makkonen & Olkkonen's (2017) framework for interactive value formation (IVF) among interorganizational relationships contributes towards understanding service systems as well as resource integration; both aspects being aligned with those espoused by IVAm's principles (Makkonen & Olkkonen, 2017).

Dong (2011) carried out a study on decision analysis systems based on interactive visual components which effectively supports analyzing and decision-making activities for enterprises in line with IVAm's effort towards improving data comprehension through cognitive processes like pattern recognition and mental model building (Dong, 2011). Additionally, Andrienko & Andrienko (2013) have developed a visual analytics framework for spatio temporal analysis and modeling where interactive visualization techniques are combined with computational methods thus supporting IVAm's approach to data analysis (Andrienko & Andrienko, 2013).

IMPLEMENTATION STRATEGIES

Modern data analysis involves the integration of interactive tools into quantitative research designs, especially for creating dynamic visualizations. Tools such as Tableau, R with Shiny and D3.js have a variety of functionalities that are necessary for interactive and engaging visualizations. User experience is at the heart of designing these kinds of visualizations; they should be intuitive, informative and engaging.

- **Integration of Interactive Tools**

Researchers need to incorporate programs like Tableau, R with Shiny or D3.js for creating dynamic visualizations. These tools can create interactive and engaging visualizations among others. For instance, R with the shiny package can create dynamic, interactive figures for scientific data visualization supporting understanding of health and wellness in individuals and communities (Heinsberg et al., 2022). Statistical data modeling using R and Shiny has been enhanced by interactive visualization tools reducing the time required to build visually interactive applications (Khedr & Hilal, 2021). Additionally, using a web application framework like Shiny under the R statistical platform helps to quickly generate interactive data visualizations in psychology research (Ellis & Merdian, 2015).

When designing visualizations, it is important designers consider how users will interact with them hence making sure they are easy to navigate through as well as interpretive (Khadka et al., 2019). By blending data together in Tableau one can create mashups of structured heterogeneous datasources into one single visualization without any upfront integration effort required (Morton et al., 2012). In animal science, scientific discoveries can be made by means of interacting with an animated representation created using r shiny library (Morota, 2021). Dashboards can be built in Power BI or Tableau while reports created within Excel files if these programs work together with R (Nair, Krishna & Srivastava, 2019).

- **Transparency in Methodology**

Research credibility and reproducibility require transparent reporting of methodologies and data sources under IVAm. In some cases, transparent research practices have resulted in thoroughly evaluated and potentially reproduced data thereby improving the quality of Human-Computer Interaction (HCI) research among others (Wacharamanotham et al., 2022). Communication and understanding are supported by transparent methodology and data visualizations which inform study design as well as analysis decisions (Gatto et al., 2022). For instance, this kind of transparency is paramount when communicating findings in qualitative research where Computer-Assisted Qualitative Data Analysis Software (CAQDAS) usage varies depending on the research methodology employed(Bringer et al., 2004). Methods results assumptions can be better communicated to industrial ecology practitioners using IVAm resulting into more transparency reproducibility open science (Font Vivanco et al., 2018). The necessity for clear open reporting of research processes has been emphasized across diverse fields including child adolescent mental health (Spreckelsen, 2018).

- **Feedback and Iteration**

In IVAm continuous feedback from users helps refine visualization tools. This iterative process ensures that they remain relevant and effective enough in meeting diverse audience needs. Eye-hand coordination is supported by feedback in the IVAm through well chosen interaction metaphors as well as providing rapid consistent feedback (Ware, 2021). For example, interactive meta-analyses facilitate faster consensus building because they reveal how much our decisions would change if we use different criteria for selecting studies or analyzing them further aiding in directing future resources towards areas where most is known already (Ahern et al., 2020). This iterative process is similar to what happens when using Bayesian probability principles thus providing a framework for rational reasoning while countering biases within qualitative research designs too(Fairfield & Charman, 2019). In this case, it means that visualizations and methodologies are improved continuously based on user input as well as evolving research needs.

POTENTIAL IMPACTS, CHALLENGES, AND FUTURE DIRECTIONS

- **IVAm Potential Applications**

IVAm has vast potential applications in policy-making, education, public discourse, and various industries. Policymakers and stakeholders can be empowered by interactive visualizations through accessible insights that are actionable for data-driven decision-making across different policy domains like healthcare, education as well as environmental protection. IVAm can be embedded into educational curricula for students to equip themselves with data literacy skills; critical thinking can become better improved while complex concepts will be understood more deeply through their interactive exploration or analysis. With democratized access to data and interactive tools for exploration, IVAm might help promote informed public discourse about such important issues empowering citizens therefore allowing them to engage with data so as to form conclusions on their own. From healthcare and finance to marketing and media, IVAm can find its use in improving data-driven decision-making, optimizing processes enhancing customer experience driving innovation among other things that may occur in different sectors.

- **Challenges**

Despite its vast potential there exists some challenges which need addressing before wide adoption of this technology takes place effectively. Some researchers and users may have limited access to appropriate technology especially those who do not possess expertise Interactive Visualization Tools due lack resources Addressing these limitations requires promoting technological accessibility as well as training programs meant equipping researchers plus users necessary skills (Meyer et al., 2012). For efficient implementation it would be necessary train how interact visualizations such that they can fully utilize capabilities provided by model Developing user-friendly interfaces providing educational resources fostering collaboration between researchers users are some ways through which gap bridged (Pirrò et al., 2012). However, careful attention must be paid towards data privacy transparency methodology potential biases embedded visualizations order uphold ethical research practices Developing robust ethical guidelines fostering open communication employing responsible techniques analysis are vital addressing these concerns (Bertini et al., 2011).

- **Potential Impacts**

The IVAm has the potential to significantly impact the field of quantitative research by revolutionizing data presentation, facilitating deeper understanding, and broadening audience reach. This model integrates interactive and dynamic visualization techniques that move away from traditional static graphs towards more engaging formats which are also accessible. IVAm has the potential to transform how quantitative data is presented, shifting from static graphs to dynamic, interactive formats. This change can make data more engaging and easier to understand thereby enhancing its impact Interactive visualization models like IVAm can revolutionize data presentation in quantitative research using techniques such as self-organizing feature maps which generate three-dimensional color-coded surface models (Sangole & Knopf, 2002) promoting deeper understanding as well as increasing audience reach Additionally computational analysis combined with visualization interaction this technology could facilitate its use in other areas within the same field (Kehrer & Hauser, 2013).

The model can facilitate the deep understanding of complex data, thereby helping in making more informed decisions and research conclusions. IVAm can fill the gap between complicated research findings and practical application by making data more accessible and engaging. Other than understanding, diagnosing, and refining machine learning models, interactive visualization and analysis models such as IVAm can efficiently solve real life AI and data mining problems (Liu et al., 2017). Interactive visual analytics (IVA) may help a data scientist develop smartphone health sensing tools or an analyst make sense of patient behaviors through additional contextual and semantic information (Mansoor et al., 2021).

By making data more accessible, IVAm can widen the scope of quantitative research thereby influencing policy-making, education, and public debates. This expansion implies that decisions are better informed at different levels while society becomes more knowledgeable about statistics. Font Vivanco et al. (2018) notes that IVAm can hugely expand the reach and impact of research work while promoting transparency, reproducibility, open science as well as improving clarity in presenting quantitative studies. Jing et al. (2017) argue that interactive visual analysis using embedded network visualization could reveal temporal patterns without occlusion in complex datasets hence revolutionizing how data is analyzed and presented.

- **Future research directions**

To further refine and validate IVAm, few areas may be considered for future investigations – developing new techniques; investigating long-term impacts; exploring ethical implications; evaluating effectiveness in collaboration and knowledge exchange. Developing new interactive visualization techniques/tools tailored for specific research contexts: This may involve exploring advanced visualization methods; integrating AI & machine learning for automated analysis; designing tools specific to diverse research disciplines. Investigating the long-term impact of IVAm on user engagement, learning outcomes & decision-making across various settings: Such studies would inform on how to implement IVAm properly, factors influencing its effectiveness, and broader societal outcomes affected. Exploring the ethical implications of interactive data visualization & developing best practices for responsible use: Such researches can address concerns regarding data privacy, bias or misinformation hence ensuring ethical use of IVAm. Evaluating the effectiveness of IVAm in promoting collaboration & knowledge exchange across diverse stakeholder groups: This would involve looking at ways in which IVAm can encourage interdisciplinary research; including the public in research processes and facilitating knowledge dissemination towards wider societal gains.

Academic Discourse and Collaborative Development: IVAm is a new concept within quantitative research that has entered into academic discourse. Through infusion of different perspectives and expertise, it is possible for IVAm to evolve through diverse academic conversations and explorations. This open dynamic discourse plays a critical role in understanding better what IVAm can do as well as identifying innovative applications in various fields (Miller et al., 2019). Incorporation of feedbacks, criticisms or fresh ideas coming from wide academic community will help shape future directionality of IVAm thereby maintaining its significance and efficiency within rapidly changing dataset landscape (Blei et al., 2003).

CONCLUSION

This is a clear indication that IVAm is a significant advancement in quantitative research methodologies. IVAm enhances data interpretability and presentation thereby making it more accessible and engaging, aligning with the digital era. The idea of IVAm implies a change in focus from user engagement to interactive exploration of data. This approach will empower different groups of people while leading to better decisions based on facts in different sectors. With time, IVAm can transform research practices so as to engage more stakeholders in its data-driven world.

REFERENCES

1. Ahern, T., MacLehose, R., Haines, L. L., Cronin-Fenton, D., Damkier, P., Collin, L., Lash, T. (2020). Improving the transparency of meta-analyses with interactive web applications. *BMJ Evidence-Based Medicine*, 26, 327-332. https://doi.org/10.1136/bmjebm-2019-111308
2. Andrienko, N., & Andrienko, G. (2013). A visual analytics framework for spatio-temporal analysis and modelling. *Data Mining and Knowledge Discovery*, 27(1), 55-83. https://doi.org/10.1007/s10618-012-0285-7
3. Angelini, M., Daraio, C., Lenzerini, M., Leotta, F., & Santucci, G. (2020). Performance model's development: a novel approach encompassing ontology-based data access and visual analytics. *Scientometrics*, 125, 865-892. https://doi.org/10.1007/s11192-020-03689-x
4. Ayad, A., Marsit, I., Loh, J., Omri, M., & Mili, A. (2019). Quantitative Metrics for Mutation Testing. *Proceedings of the 14th International Conference on Software Technologies*. https://doi.org/10.5220/0007841800490059

5. Bach, B. (2016). Unfolding Dynamic Networks for Visual Exploration. IEEE Computer Graphics and Applications, 36, 74-82. https://doi.org/10.1109/MCG.2016.32
6. Bajaj, C. (1997). Visualization and Querying of Scalar, Vector, and Tensor Field Data. https://doi.org/10.21236/ada379438
7. Bringer, J., Johnston, L., Brackenridge, C. (2004). Maximizing Transparency in a Doctoral Thesis1: The Complexities of Writing About the Use of QSR*NVIVO Within a Grounded Theory Study. *Qualitative Research*, 4, 247-265. https://doi.org/10.1177/1468794104044434
8. Camilleri, M., & Camilleri, A. (2017). Digital Learning Resources and Ubiquitous Technologies in Education. *Technology, Knowledge and Learning*, 22(1), 65-82. https://doi.org/10.1007/s10758-016-9287-7
9. Chmielewski, M., Sapiejewski, K., & Sobolewski, M. (2019). Application of augmented reality, mobile devices, and sensors for a combat entity quantitative assessment supporting decisions and situational awareness development. *Applied Sciences (Basel, Switzerland)*, *9*(21), 4577. https://doi.org/10.3390/app9214577
10. Cleveland, W., & McGill, R. (1984). Graphical Perception: Theory, Experimentation, and Application to the Development of Graphical Methods. *Journal of the American Statistical Association*, 79(387), 531-554. https://doi.org/10.1080/01621459.1984.10478080
11. Cope, D. (2014). Computer-assisted qualitative data analysis software. *Oncology nursing forum*, 41(3), 322-3. https://doi.org/10.1188/14.ONF.322-323
12. Davidson, J., Paulus, T., & Jackson, K. (2016). Speculating on the Future of Digital Tools for Qualitative Research. *Qualitative Inquiry*, 22(6), 606-610. https://doi.org/10.1177/1077800415622505
13. Díez-Garrido, M. (2017). La transparencia del Partido Popular y Ciudadanos en las campañas electorales de 2015 y 2016. *Revista Digital*. https://doi.org/10.7203/RD.V2I3.75
14. Dong, T. (2011). Research on Decision Analysis System Based on Interactive Visual Components. *Chinese Journal of Computers*. https://doi.org/10.3724/sp.j.1016.2011.00555
15. Ellis, D., & Merdian, H. (2015). Thinking Outside the Box: Developing Dynamic Data Visualizations for Psychology with Shiny. *Frontiers in Psychology*, 6. https://doi.org/10.3389/fpsyg.2015.01782
16. Fairfield, T., Charman, A. (2019). A Dialogue with the Data: The Bayesian Foundations of Iterative Research in Qualitative Social Science. *Perspectives on Politics*, 17, 154-167. https://doi.org/10.1017/S1537592718002177
17. Font Vivanco, D., Hoekman, P., Fishman, T., Pauliuk, S., Niccolson, S., Davis, C., Makov, T., Hertwich, E. (2018). Interactive Visualization and Industrial Ecology: Applications, Challenges, and Opportunities. *Journal of Industrial Ecology*. https://doi.org/10.1111/jiec.12779
18. Gatto, N., Wang, S. V., Murk, W., Mattox, P., Brookhart, M., Bate, A., Schneeweiss, S., Rassen, J. (2022). Visualizations throughout pharmacoepidemiology study planning, implementation, and reporting. *Pharmacoepidemiology and Drug Safety*, 31, 1140-1152. https://doi.org/10.1002/pds.5529
19. Gicheru, J., & Kariuki, D. R. P. (2019). Influence of dynamic capabilities on performance of commercial banks in Kenya. *Strategic Journal of Business & Change Management*, *6*(2). https://doi.org/10.61426/sjbcm.v6i2.1216
20. Gierlich-Joas, M., Hess, T., & Neuburger, R. (2020). More self-organization, more control—or even both? Inverse transparency as a digital leadership concept. *Business Research*. https://doi.org/10.1007/s40685-020-00130-0
21. Gomber, P., Koch, J.-A., & Siering, M. (2017). Digital Finance and FinTech: current research and future research directions. *Journal of Business Economics*, 87(5), 537-580. https://doi.org/10.1007/S11573-017-0852-X
22. Heinsberg, L. W., Koleck, T. A., Ray, M., Weeks, D., & Conley, Y. (2022). Advancing Nursing Research Through Interactive Data Visualization With R Shiny. *Biological Research For Nursing*, 25, 107-116. https://doi.org/10.1177/10998004221121109
23. Hurst, A., Gajos, K. Z., Findlater, L., Wobbrock, J., Sears, A., & Trewin, S. (2011). Dynamic accessibility: accommodating differences in ability and situation. *CHI '11 Extended Abstracts on Human Factors in Computing Systems*. https://doi.org/10.1145/1979742.1979589

24. Iqbal, T., & Ahmad, S. (2022). Transparency in humanitarian logistics and supply chain: the moderating role of digitalisation. *Journal of Humanitarian Logistics and Supply Chain Management*. https://doi.org/10.1108/jhlscm-04-2021-0029
25. Isenberg, P., Elmqvist, N., Scholtz, J., Cernea, D., Ma, K., Hagen, H. (2011). Collaborative visualization: Definition, challenges, and research agenda. Information Visualization, 10, 310-326. https://doi.org/10.1177/1473871611412817
26. Jern, M. (2008). Collaborative Explorative Data Analysis Applied in HTML. https://doi.org/10.1007/978-3-540-88011-0_5
27. Jia, Q., Wei, L., & Li, X. (2019). Visualizing sustainability research in business and management (1990–2019) and emerging topics: A large-scale bibliometric analysis. *Sustainability*, *11*(20), 5596. https://doi.org/10.3390/su11205596
28. Jing, M., Li, X.-q., & Hu, Y. (2017). Interactive Temporal Visualization of Collaboration Networks. https://doi.org/10.1007/978-3-319-77383-4_70
29. Johansson, S., & Jern, M. (2007). GeoAnalytics visual inquiry and filtering tools in parallel coordinates plots. https://doi.org/10.1145/1341012.1341055
30. Kehrer, J., & Hauser, H. (2013). Visualization and Visual Analysis of Multifaceted Scientific Data: A Survey. *IEEE Transactions on Visualization and Computer Graphics*, 19, 495-513. https://doi.org/10.1109/TVCG.2012.110
31. Khedr, A., & Hilal, S. (2021). Interactive Visualization for Statistical Modelling through a Shiny App in R. *2021 International Conference on Data Analytics for Business and Industry (ICDABI)*, 332-337. https://doi.org/10.1109/ICDABI53623.2021.9655841
32. Linsner, S., Kuntke, F., Steinbrink, E., Franken, J., & Reuter, C. (2021). The Role of Privacy in Digitalization – Analyzing Perspectives of German Farmers. *Proceedings on Privacy Enhancing Technologies*, 2021, 334-350. https://doi.org/10.2478/popets-2021-0050
33. Liu, S., Wang, X., Liu, M., & Zhu, J. (2017). Towards better analysis of machine learning models: A visual analytics perspective. *ArXiv*, abs/1702.01226. https://doi.org/10.1016/J.VISINF.2017.01.006
34. Lundblad, P., & Jern, M. (2013). Geovisual Analytics and Storytelling Using HTML5. 2013 17th International Conference on Information Visualisation. https://doi.org/10.1109/IV.2013.35
35. Makkonen, H., & Olkkonen, R. (2017). Interactive value formation in interorganizational relationships. *Marketing Theory*, 17(4), 517-535. https://doi.org/10.1177/1470593117699661
36. Mansoor, H., Gerych, W., Alajaji, A., Buquicchio, L., Chandrasekaran, K., Agu, E., & Rundensteiner, E. A. (2021). Visual Analytics of Smartphone-Sensed Human Behavior and Health. *IEEE Computer Graphics and Applications*, 41, 96-104. https://doi.org/10.1109/MCG.2021.3062474
37. Maulana, A., Putri, A. D., & Yulia. (2019). Development of digital currency technology. *Journal of Physics: Conference Series*, 1175. https://doi.org/10.1088/1742-6596/1175/1/012205
38. Meyer, D., & Kieras, D. (1997). A computational theory of executive cognitive processes and multiple-task performance: Part 1. Basic mechanisms. *Psychological Review*, 104(1), 3-65. https://doi.org/10.1037/0033-295X.104.1.3
39. Morota, G. (2021). 79 Statistical Graphics and Interactive Visualization in Animal Science. *Journal of Animal Science*. https://doi.org/10.1093/jas/skab235.079
40. Morton, K., Bunker, R., Mackinlay, J., Morton, R., & Stolte, C. (2012). Dynamic workload driven data integration in tableau. *Proceedings of the 2012 ACM SIGMOD International Conference on Management of Data*. https://doi.org/10.1145/2213836.2213961
41. Nair, P., Krishna, J., & Srivastava, D. K. (2019). Visual Analytics Toward Prediction of Employee Erosion Through Data Science Tools. *Information and Communication Technology for Sustainable Development*. https://doi.org/10.1007/978-981-13-7166-0_71
42. Nasiri, M., Saunila, M., Ukko, J., Rantala, T., & Rantanen, H. (2020). Shaping Digital Innovation Via Digital-related Capabilities. *Information Systems Frontiers*. https://doi.org/10.1007/s10796-020-10089-2
43. Naslund, J., Gonsalves, P., Gruebner, O., Pendse, S. R., Smith, S. L., Sharma, A., & Raviola, G. (2019). Digital Innovations for Global Mental Health: Opportunities for Data Science, Task Sharing,

and Early Intervention. *Current Treatment Options in Psychiatry*, 6, 337-351. https://doi.org/10.1007/s40501-019-00186-8

44. O'Halloran, K., Tan, S., Pham, D.-S., Bateman, J., & Vande Moere, A. (2018). A Digital Mixed Methods Research Design: Integrating Multimodal Analysis With Data Mining and Information Visualization for Big Data Analytics. *Journal of Mixed Methods Research*, 12(1), 11-30. https://doi.org/10.1177/1558689816651015
45. Palha, S. (2017). Students learning with Interactive Virtual Math: an exploratory study in the classroom. https://doi.org/10.3895/etr.v1n1.5990
46. Parsons, P. C., & Sedig, K. (2014). Adjustable properties of visual representations: Improving the quality of human-information interaction. *Journal of the Association for Information Science and Technology*, 65(3). https://doi.org/10.1002/asi.23002
47. Rani, U., & Furrer, M. (2020). Digital labour platforms and new forms of flexible work in developing countries: Algorithmic management of work and workers. *Competition & Change*, 25, 212-236. https://doi.org/10.1177/1024529420905187
48. Ross, P. T., & Zaidi, N. L. B. (2019). Limited by our limitations. *Perspectives on Medical Education*, 8, 261-264. https://doi.org/10.1007/s40037-019-00530-x
49. Sandelowski, M. (2005). Book Review: Interactive Qualitative Analysis: A Systems Method for Qualitative Research. *Qualitative Health Research*, 15(5), 719-720. https://doi.org/10.1177/1049732305015005011
50. Sangole, A., & Knopf, G. (2002). Representing High-Dimensional Data Sets as Closed Surfaces. *Information Visualization*, 1, 111-119. https://doi.org/10.1057/palgrave.ivs.9500015
51. Sedig, K., & Parsons, P. C. (2013). Interaction Design for Complex Cognitive Activities with Visual Representations: A Pattern-Based Approach. *AIS Transactions on Human-Computer Interaction*, 5(2), 84-133. https://doi.org/10.17705/1THCI.00055
52. Spreckelsen, T. (2018). Editorial: Changes in the field: banning p-values (or not), transparency, and the opportunities of a renewed discussion on rigorous (quantitative) research. *Child and Adolescent Mental Health*, 23(2), 61-62. https://doi.org/10.1111/CAMH.12277
53. Tiwasing, P., Galloway, L., Refai, D., Kevill, A., Kromidha, E., & Pattinson, S. (2023). The International Journal of Entrepreneurship and Innovation editors' series: Advancing quantitative research in entrepreneurship. *The International Journal of Entrepreneurship and Innovation*, 24(1), 3-6. https://doi.org/10.1177/14657503221148571
54. Tran, B. (2019). The Nature of Research Methodologies. *Advances in Library and Information Science*. https://doi.org/10.4018/978-1-5225-2255-3.CH585
55. Viola, L. (2020). Replication, evaluation and quantitative analysis in the DH era: Transparent digital practices and lessons learned from the development of the Geo News Miner. https://doi.org/10.5281/ZENODO.3859535
56. Wacharamanotham, C., Yang, F., Pu, X., Sarma, A., Padilla, L. M. K. (2022). Transparent Practices for Quantitative Empirical Research. *CHI Conference on Human Factors in Computing Systems Extended Abstracts*. https://doi.org/10.1145/3491101.3503760
57. Wan, Y., McDole, K., & Keller, P. J. (2019). Light-sheet microscopy and its potential for understanding developmental processes. *Annual Review of Cell and Developmental Biology*, *35*(1), 655–681. https://doi.org/10.1146/annurev-cellbio-100818-125311
58. Ware, C. (2021). Interacting with Visualizations. *Information Visualization*. https://doi.org/10.1016/B978-0-12-381464-7.00010-7