What Can Educational Science Offer Visualization? A Reflective Essay

Konrad Schönborn [*]
Linköping University

Lonni Besançon [†]
Linköping University

ABSTRACT

In this reflective essay, we explore how educational science can be relevant for visualization research, addressing beneficial intersections between the two communities. While visualization has become integral to various areas, including education, our own ongoing collaboration has induced reflections and discussions we believe could benefit visualization research. In particular, we identify five key perspectives: surpassing traditional evaluation metrics by incorporating established educational measures; defining constructs based on existing learning and educational research frameworks; applying established cognitive theories to understand interpretation and interaction with visualizations; establishing uniform terminology across disciplines; and, fostering interdisciplinary convergence. We argue that by integrating educational research constructs, methodologies, and theories, visualization research can further pursue ecological validity and thereby improve the design and evaluation of visual tools. Our essay emphasizes the potential of intensified and systematic collaborations between educational scientists and visualization researchers to advance both fields, and in doing so craft visualization systems that support comprehension, retention, transfer, and critical thinking. We argue that this reflective essay serves as a first point of departure for initiating dialogue that, we hope, could help further connect educational science and visualization, by proposing future empirical studies that take advantage of interdisciplinary approaches of mutual gain to both communities.

1 INTRODUCTION

What an exhilarating time to be immersed in visualization. The community is currently plunged in the surge of big data and open data initiatives, significant advancements in high-performance computing, new ways to interact with virtual and augmented realities, as well as rapid integration of AI and Large Language Models into visualization systems.

Importantly, visualization systems are an integral part of solving problems through exciting interdisciplinary connections that include, inter alia, medical diagnostics [77], genomics [59], molecular dynamics [93], physics [97], and astronomy [15], with recent particular momentum around how AI-driven visualization can provide new routes of discovery and interaction [49, 102]. Visualization is also becoming important for understanding social trends and behavioral relationships, with swift parallel advancements in how human-computer interaction can be effectively complemented with user-centered design to create useful tools for different domain experts (e.g., [77]). Visualization is also playing a key role in the open data movement and other citizen science initiatives. In other interdisciplinary applications, the convergence of data science and visualization has opened new ways for interpreting information, not least by engaging the public with science in novel and engaging ways [86, 61]. Finally, visualization has manifested as a cross-disciplinary tool for confronting global and complex societal challenges such as formulating strategies for communicating about or mitigating climate change [9, 44], and confronting pandemics [63].

Going beyond the interdisciplinary nature that we highlight above, visualization is also a crucial component for education purposes [84, 72, 70, 76, 95]. For instance, visualization can enhance learning by making complex concepts accessible, with a complementary wealth of educational research demonstrating improved knowledge acquisition [55] and retention [66, 67]. Multiple studies have highlighted how emerging interactive visualization can increase engagement and stimulate curiosity [73]. In addition, there is a growing body of work indicating how adaptive visualizations integrated with real-time feedback can support students' understanding of complex scientific concepts [64]. On this note, visualization tools also contribute to instructional design and assessment of student performance with emergent digitalization of education initiatives [48, 39, 100]. There is also growing emphasis on how engaging with visualizations can help support students' critical thinking, and thereby aid in developing analytical and problem-solving skills, as well as facilitate collaborative learning [83]. Furthermore, visualization is a powerful pedagogical intervention that can serve diverse learning needs, and make learning more inclusive by transcending language differences and other common educational challenges [33]. Moreover, there are several further applications of visualization for education that include skills for creating meaningful visualizations, and the importance of models and modeling elements of visualization for STEM education, where it can act as a bridge to connect scientific phenomena, mathematical relationships, engineering design, and technological processes [41, 40].

While the influence of visualization *on* and *for* education is well-documented in the literature in both research domains, we raise a different question: what can educational science offer visualization? Specifically, in posing this question, we mean perspectives from educational science research that could influence or have relevance for the visualization community and the nature of its research. While also certainly noteworthy, in this essay we do *not* denote pedagogical interventions for improving teaching and learning about visualization per se (which was the focus of the EduVis workshop last year[1]). Rather, we focus on and probe the role and implications of educational science research *for* visualization research. So, in stating the problem motivation of this reflective essay, although educational science has made paramount inroads into, for example, our understanding of cognitive development, integration of educational technology into practice, and development of strategies for inclusive education, there has been limited systematic interrogation of what educational science can bring to the field of visualization and its community. Therefore, in commencing reflection on this question, this essay:

[*]e-mail: konrad.schonborn@liu.se
[†]e-mail: lonni.besancon@gmail.com

[1]https://ieee-eduvis.github.io/2023.html

- Exposes five perspectives from educational science of relevance to the visualization field;
- Considers the implications of these perspectives for visualization research;
- Anticipates future empirical endeavours that could intersect educational research perspectives with visualization research.

Rising to these issues is very close to our hearts at the Visual Learning and Communication research group in Norrköping, Sweden. We have the privilege to work at the interface of visualization and learning, driven by the inquiry, how does visualization impact learning? To answer this question empirically necessitates examining aspects of the five perspectives raised in this essay. We do so through a unique combination of two positions: The first author brings expertise from educational research, focusing on visual learning processes, cognitive theory, and pedagogical frameworks, in considering what these might mean for the visualization discipline; The second author contributes experience from what current knowledge about user studies and visualization research might mean for the contribution of educational research to the visualization discipline.

2 Educational Science meets Visualization

Based on our joint interests, current work and intersecting expertise, we are of course aware of multiple visualization papers that focus on educational outcomes, and education-orientated objectives. This is particularly the case for us, where we also conduct research within a division that hosts the Visualization Center C in Norrköping, Sweden, a digital science center that uses interactive visualization to communicate and provide the public with access to interpreting complex scientific phenomena. As part of this endeavor, we have contributed to the development of visualization exhibits and penned several scientific reports on the topic (e.g., [104, 47], and are aware of other exciting work within the domain (e.g., [19, 80, 45, 53, 60]. However, despite these encouraging directions, we argue that the intersection of educational science and visualization research is still in its early stages, an overlap that we believe yields promising prospects for future development.

A rapid yet enlightening example search on the IEEE Xplore database during the penning of this essay highlights that the term "education" in IEEE TVCG is only present in approximately 10 journal articles [1, 7, 26, 27, 37, 42, 74, 79, 82, 87]. Of these, only 5 emanate from the visualization research community [1, 7, 37, 42, 87], while the other 5 stem from the Augmented or Virtual Reality (AR/VR) track of the journal [26, 27, 74, 79, 82]. Four of the 10 papers focus on visualization education [1, 7, 37, 42], as stated previously, concerned with efforts on improving teaching and learning within the field of visualization, while 1 proposes an interactive system to facilitate the creation of educational materials [87]. Please do note that this search is not intended as exhaustive, nor do we claim that the chosen source is the only representative venue of visualization research. We only apply it here as a representative example of the dearth of the presence of educational science in the visualization field. This example search is of course also assuming that an educational researcher searching for educational science driven research in visualization will often seek journal articles, and is perhaps unlikely to search for other potentially relevant conference proceedings of the ACM (e.g., CHI conference) or workshop papers (e.g., the BELIV workshop series) from the visualization community.

Convergence of each author's respective thinking about the problem statement of this essay has identified five perspectives of educational science that we shall reflect upon. The following reflections are born out of continued current collaboration, and shared discussions gathered through each author's specialized knowledge from each parent discipline, and observations about how each of these research disciplines have developed in relation to the nature of visualization. The reflections offer a starting point for prompting further discussion and are not meant to serve as an all-encompassing review.

Firstly, *surpassing task completion time and accuracy* considers the potential of established educational research measures for visualization research. Secondly, *gaining insight in light of existing educational constructs*, considers what is meant by terms such as "insight" in relation to established learning nomenclature. *Applying cognitive processes and learning theory* serves as the third perspective, where the use of existing knowledge about human cognition and learning can influence aspects of visualization research. Fourthly, given both the separate and similar use of terms such as "visual literacy" (see e.g., [83]) and "visualization literacy" (see e.g., [20]) to (sometimes) denote overlapping (or separate) assertions, we discuss a potential need for *savoring and establishing existing terminology*. Lastly, we argue for taking advantage of *increasing interdisciplinary aspects of convergence* by building on and empirically connecting newly emerging paradigms such as "exploranation" from both educational science and visualization perspectives.

3 Exposing Five Perspectives from educational science

We now describe how each of the five educational science perspectives are, in our opinion and observed experiences, of potential high relevance for visualization research.

3.1 Surpassing Task Completion Time and Accuracy

In the fields of Human-Computer Interaction (HCI) and visualization, a recurring evaluation format focuses on measuring task completion time and accuracy or errors [54]. While certainly established and respected, classical evaluations are sometimes inappropriate for a variety of visualization research that seeks to discover domain expert system design or collaboration patterns (see, e.g., [11, 54, 90]). This observation has driven the visualization research community to reflect on how they could design novel evaluation methods that would go beyond the simple – and often status quo – usability measures of time and errors, perhaps most notably through the BELIV workshop series (see e.g., [12, 13]). This workshop series has helped the community reflect upon and consider new evaluation strategies to, for instance, study inclusion and accessibility [3], evaluate trust [31], or analyse interaction logs of exploratory visualizations [32, 105].

Such workshop series have facilitated the broadening of the visualization community's understanding and treatment of "evaluation" to include other measures of interest, methodologies, or application domains. However, established principles of educational research have not yet been considered in earnest. For example, our analysis of the BELIV workshop proceedings does not reveal a single paper that takes educational science as its foundation premise. That said, an example paper that would closely relate to educational science is Burns et al. [22], which considers Bloom's taxonomy [14] in providing a framework to evaluate knowledge acquisition with visualizations. In this paper, the authors aim to construct a set of questions that would evaluate and distinguish between a range of different understanding levels: from a person's perceptual understanding of a visualization to how they would apply learned information from the visualization to a real-world problem. Through such examples, we opine that the visualization community might benefit from more education-grounded and established learning measures established in education research. For instance, knowledge retention (which is mentioned in several TVCG papers outside of "pure" visualization research, e.g., [26, 27]), has been a classic education measure for close to a century, while measures around "knowledge transfer"

[85] are often seen as the ultimate standard for testing true learning in educational science. While it appears that the visualization community has recently included more evaluations and discussions that are somewhat close to the notion of "knowledge transfer" (see e.g., [5, 17, 65, 58, 98], we posit that there should be a stronger emphasis on the inclusion of such objectives for visualization researchers. Lastly, although we are excited to see its emergence in several visualization quarters, and paramount to many of our own research pursuits, e.g., [88, 84] we strongly advocate for qualitative research methods [106, 90, 69], many of which are deeply and traditionally recognized in educational research. Qualitative and interpretivist methods such as clinical think-aloud interviews [88, 86], observation, focus group methods, and design study methodology [90, 69], allow for in-depth exploration, allowing for the investigation of context-specific meanings that also offer flexibility in iterative research design [61].

While we agree that there is an emerging concerted effort from visualization researchers to go beyond the most direct evaluations of visualizations and their understanding as visible in the papers we identify above, we look forward to discussing how we could approach this as a joint systematic effort between our two communities.

3.2 Gaining Insight in Light of Existing Constructs

In the realm of education research, several data collection and analytical approaches have been developed since the late 19th century with the vision of crafting valid measures of established constructs. Surveys, structured interviews, observation, validated tests and case studies are all examples of methods implemented to yield information that can be mapped to learning processes, learning outcomes, pedagogical effectiveness, as well as intrinsic motivation and self-efficacy [81]. For example, it is commonplace for educational researchers to systematically define the "learning process" or "learning outcome" or "learning performance" that is being empirically pursued. In providing an example on this point, visualization researchers often use the term *insight* to demarcate meaningful, beneficial or positive outcomes in relation to some sort of comprehension, awareness, or realization that might be associated with a deeper understanding. However, it is rare that the nature of such "insight" or what learning or cognitive components it constitutes are formally operationalized in visualization research communications (some exceptions can however be found, see, e.g., [74, 79]). This is especially in relation to the data collection and analytical procedures employed. In this regard, educational researchers would wonder, what in particular about "insight" that is being sought? How do the researchers know that they are actually measuring "insight". How does "insight" relate to established educational, cognitive and learning constructs of knowledge acquisition, learning transfer, or application of knowledge?

Education and learning researchers could provide established directions for how to operationalize and define constructs that are in question. This is especially important when "strengths/advantages" or "limitations/disadvantages" claims are made about human or user perception, interaction or interaction with a visualization system. Such clarity can also facilitate the application of research findings to real practice and contexts. In this sense, education and learning researchers often pursue "ecological validity" [106], which refers to the extent to which findings can be applied to real-life settings or situations, and whether they reflect the complexities of real-world situations. We deem ecological validity a crucial criterion in visualization research, since visualization research often aims to represent complex data that is meaningful to users in real world settings. It also seeks merit in being able to provide useful information about the effectiveness of visualization in supporting cognitive tasks such as decision-making and behavior.

While past research has highlighted that visualization education may "benefit from the integration of pedagogical strategies for teaching abstract concepts with established interactive visualization techniques" [2], we hope that our arguments highlight that *visualization research* may also benefit from integrating existing learning and educational measures into study design and analysis.

3.3 Applying Cognitive Processes and Learning Theory

Developments in cognitive science played a pivotal role in the establishment of educational research as a realm of empirical inquiry. Cognitive science provides frameworks for considering human perception, information-processing architecture and problem-solving strategies, which in turn, can be mapped onto hypothesizing about learning processes and how understanding is acquired. A wonderful example in the context of perception and comprehension of visual information is the seminal work of Larkin and Simon [56] who beautifully demonstrated the power of spatial visualization. Following on this track is the huge influence of cognitive load theory [24] and multimedia learning [66] in providing powerful access points for investigating and analyzing how people learn and construct understanding from visualized information. Typical tenets from cognitive multimedia learning theory [66, 67] combine the science of learning and instructional affordances. For example, information that is of no use to a learning process is said to be extraneous, since it vies for limited cognitive resources in working memory. Hence, reducing extraneous processing can be made possible through various established empirical principles that include the redundancy principle (humans learn more effectively from visualizations accompanied by narration compared to those with text) and the spatial contiguity principle (humans learn more effectively when text and visualizations are in near proximity rather than far apart on the search space). In this regard, our own work [89] has proposed the notion of a visuohaptic modality effect, where the dual-mode visuohaptic experience of interpreting a submicroscopic concept might help reduce cognitive overload by offloading demanding visual processing through haptic and visual referential connections.

Recently, the application of embodied cognition in the context of learning with interactive visualization environments, e.g. [89, 38] provides perspectives that go beyond the mind alone by positing that sensory experiences, motor actions and interactions within or with a system, also influence the nature of knowledge acquisition and learning [101]. At the same time, in applying cognitive processes, researchers should also take heed of affective learning intents and objectives of visualizations [58]. These include perspectives around outcomes resulting from engaging the viewer with a particular subject, solidifying an opinion, or prompting some kind of action. It is our view that acknowledging cognitive theory in visualization research provides a means into the nuances of human perception, interpretations and interactions with visual information, which can assist in providing a frame for developing visualizations that enhance learning and educational impact.

Coupled to influences from cognition, educational psychology has strengthened the genre of educational research by providing tenets for how individuals and groups of individuals might learn in different environments, thus yielding potential directions for developing effective learning and teaching methods [52]. When it comes to visualization research, educational psychology can help inform the design of visualizations to be aligned with cognitive abilities and preference [51]. In doing so, efforts in visualization research can be directed to the crafting of engaging and effective visual tools that support comprehension, retention, and transfer of complex concepts.

3.4 Savoring and Establishing Existing Terminology

It is well known that vocabulary differences and esoteric jargon around concepts and principles create potential challenges both for researchers in collaborative interdisciplinary work, and for information retrieval systems when researchers search for papers that could be of relevance to their work [25, 28, 68, 75]. The educational and visualization research communities are not exempt from this issue. The ongoing collaboration and discussion between the two current authors has highlighted examples of divergences in vocabulary and nomenclature that we believe are worthy to report in this context.

The visualization community sometimes distinguishes between *visual literacy* and *visualization literacy* [20, 18, 7]. As an example, in the visualization community, visual literacy is often derived from Fransecky and Debes' definition [36]: "a person's ability to discriminate and interpret the visible actions, objects, and symbols natural or man-made, that he encounters in his environment." On the other hand, Data Visualization Literacy (DVL), sometimes penned as visualization literacy represents, "a person's ability and skill to read and interpret visually represented data in and to extract information from data visualizations" [57]. For the educational research community, the concept of visual literacy and visualization literacy would seem to overlap and both could often be considered under a "visual literacy" umbrella at large. For instance, the ERIC definition states that visual literacy is "a group of competencies that allows humans to discriminate and interpret the visible action, objects, and/or symbols, natural or constructed, that they encounter in the environment" [94] and other definitions include "the ability to 'read,' interpret, and understand information presented in pictorial or graphic images" [99], "the learned ability to interpret visual messages accurately and to create such messages" [43], or "involves the ability to understand, produce, and use culturally significant images, objects, and visible actions" [34]. However, educational researchers have highlighted that the origins of the term are eclectic, the definition broad and heterogeneous [6], and also regularly overlap with other emerging related concepts such as *digital literacy* [46], or *multimodal literacy* [91]. As a whole, we support the call from Creamer et al. [29] to interrogate our operationalization of visualization literacy and meaningful methods to assess it. We also support the strong need to discuss what is meant by visualization in terms of practice and synergies with people and the future [7]. In doing so, we wish to emphasize that this should be enthusiastically pursued by also considering the existing literature in the educational sciences (e.g., [83, 6] instead of making it a visualization community effort alone.

Other terminology issues may not be as problematic as those linked to construct definition. For instance, and linked to our previous discussions in subsection 3.1, the word "evaluation" in visualization research is rather loosely used to describe any form of validation (quantitative, qualitative, ...). However, from an educational science perspective, evaluation is more limited and requires more nuanced definitions to unpack and specify which aspect(s) is/are being measured or validated. While this is not as problematic as overlapping constructs, it nevertheless reinforces existing guidelines from previous work on the need to establish a common vocabulary to further spawn successful collaborations. [28, 68, 75].

While common terminology can easily be established in some cases, more complex theoretical concepts are likely to be more challenging to find consensus across communities in a meaningful and significant manner. The main danger in this case lies in research efforts and resources that may be wasted to "reinvent the wheel" [8, 23], especially considering that the underlying cognitive processes may very well be the same.

3.5 Increasing Interdisciplinary Convergence

Visualization research is by nature, and almost by necessity, interdisciplinary [50]. In addition to collaborators in various application domains (for example, medical [77], genomics [59], molecular dynamics [93], physics [97], or astronomy [15]), visualization researchers are closely intertwined with or even contribute to disciplines related to visualization, such as computer graphics (e.g., [10]), human-computer interaction (e.g., [30]), virtual and augmented reality (e.g., [92]), or vision and cognitive sciences (e.g., [96]). Although visualization research is often undertaken to also contribute to educational goals, outcomes and pedagogical interventions with the help of educational researchers (e.g., [9, 16, 21, 103]) we argue that the visualization community would benefit from more direct and intense collaboration with educational scientists, and especially take advantage of their long tradition in mixed-method development and analysis. This is particularly true when it comes to the design and evaluation of interactive visualization with educational objectives and outcomes in mind. Herein, the enlightening illuminations on how design study as a qualitative-driven method of inquiry as articulated in [69, 90] are particularly welcomed. Such approaches can certainly contribute to the conversation about how interpretivist perspectives impact the discipline of visualization research.

There is indeed a great need of confirmed visualization systems that foster curiosity and out-of-classroom learning that are shown to benefit students [78] as well as underserved communities and networks [4]. Of promising theoretical relevance is the recently coined term "exploranation" [47, 103]– describing the convergence of domain expert exploratory visualization tools used to make sense of data with explanatory visualization tools that aim to communicate scientific concepts to the general public–almost inherently manifests as a direct call for more interdisciplinary and mixed method collaboration between educational and visualization research.

4 Conclusions and Future Intersection of Educational Research Perspectives and Visualization

In this reflective essay we set out to reflect upon how educational science research could be relevant for visualization research. We focused on five primary educational research perspectives, and what they could offer visualization researchers. Our reflections pave a departure and are not intended to be an exhaustive review, but rather the result of reflection and discussion that we have had through continued current collaboration across our two respective "parent" disciplines. As such, we first highlighted and echoed past calls for visualization research to extend evaluation methods so that they incorporate more varied and meaningful measures that are relevant to educational sciences, and therefore highly relevant from a visualization perspective in general (see subsection 3.1). For instance, we believe that classical and established knowledge retention and transfer may be of particular importance to ascertain the impact of a visualization, or of specific interaction techniques. We then argued that incorporating educational frameworks, learning taxonomies and cognitive processes (subsection 3.2 and subsection 3.3) as well as extending our vocabulary and disciplinary jargon to match existing educational research (subsection 3.4) may be beneficial in fostering ecological validity and better contribute to the body of knowledge on cognitive and learning processes. Finally, we argued that despite encouraging emerging examples of integrating educational and learning perspectives, the visualization research community could gain from more intensive and direct collaboration with educational researchers. In this spirit, education researchers could provide knowledge on mixed-method approaches for designing and investigating interactive visualizations designed with an intention to foster curiosity and engagement with complex concepts.

The rapid integration of visualization into science education resources and public spaces is moving so swiftly that educational research on identifying the benefits and limitations of emerging interactive visualization is struggling to keep up. This in itself represents a particularly exciting and promising avenue for joint work between the two communities. Science centers and museums are unique out-of-classroom learning spaces that have a strong potential to foster curiosity, renew interest in STEM, and create meaningful learning experiences [9, 47, 71, 62]. However, systematic research on this topic has been rather scarce thus far despite the promises it holds and the pivotal research challenges it proposes. In echoing the IEEE VIS 2023 Keynote, [2] we hope that pursuing the notion of exploranation in science centers can generate collaborative work that will be of interest to both communities, and eventually, strengthen our understanding and creation of joint goals, methods, and epistemology.

Based on our essay, we posit that this collaboration work may also assist both communities in promoting their research goals. Visualization researchers could implement software to analyze and understand users' interaction patterns and how they may be linked to different learning strategies [105] to help design better learning experiences with digital visualization systems. Conversely, visualization research focusing on notions of visual and visualization literacy (e.g., [2, 20, 18, 35, 57, 7] may profit from the knowledge and contributions of educational researchers. In closing, we hope that our manuscript might stimulate a more robust awareness of both communities and opportunities for a deeper educational science and visualization research collaboration. We believe that the five perspectives that we reflect upon in this essay are essential for constructing meaningful unions between our disciplines. We also hope to have provided visualization researchers with starting discussions on how educational science perspectives can align with and support contemporary visualization methods and goals.

Acknowledgments

We heartily acknowledge interactions with our colleagues in the Visual Learning and Communication (VLC) research group, division of Media and Information Technology, colleagues in the departments of Science and Technology (ITN) and Behavioural Sciences and Learning (IBL), Linköping University, as well as co-workers at Visualization Center C, Norrköping. This work is supported by the Knut and Alice Wallenberg Foundation (KAW 2019.0024), the Marcus and Amalia Wallenberg Foundation (MAW 2023.0130), and collaborative efforts at Visualization Center C.

References

[1] E. Adar and E. Lee-Robbins. Roboviz: A game-centered project for information visualization education. *IEEE Transactions on Visualization and Computer Graphics*, 29(1):268–277, 2023. doi: 10.1109/TVCG.2022.3209402 2

[2] B. Alper, N. H. Riche, F. Chevalier, J. Boy, and M. Sezgin. Visualization literacy at elementary school. In *Proc. CHI*, pp. 5485–5497, 2017. doi: 10.1145/3025453.3025877 3, 5

[3] K. Angerbauer and M. Sedlmair. Toward inclusion and accessibility in visualization research: Speculations on challenges, solution strategies, and calls for action (position paper). In *2022 IEEE Workshop on Evaluation and Beyond - Methodological Approaches for Visualization (BELIV)*, pp. 20–27, 2022. doi: 10.1109/BELIV57783.2022.00007 2

[4] L. Archer, E. Dawson, A. Seakins, J. DeWitt, S. Godec, and C. Whitby. "i'm being a man here": Urban boys' performances of masculinity and engagement with science during a science museum visit. *Journal of the Learning Sciences*, 25(3):438–485, 2016. doi: 10.1080/10508406.2016.1187147 4

[5] A. Arunkumar, L. Padilla, G.-Y. Bae, and C. Bryan. Image or information? examining the nature and impact of visualization perceptual classification. *IEEE Transactions on Visualization and Computer Graphics*, 30(1):1030–1040, 2024. doi: 10.1109/TVCG.2023.3326919 3

[6] M. D. Avgerinou and R. Pettersson. Visual literacy theory. In *Handbook of Visual Communication*. Routledge, 2024. doi: 10.4324/9780429491115-40 4

[7] B. Bach, M. Keck, F. Rajabiyazdi, T. Losev, I. Meirelles, J. Dykes, R. S. Laramee, M. AlKadi, C. Stoiber, S. Huron, C. Perin, L. Morais, W. Aigner, D. Kosminsky, M. Boucher, S. Knudsen, A. Manataki, J. Aerts, U. Hinrichs, J. C. Roberts, and S. Carpendale. Challenges and opportunities in data visualization education: A call to action. *IEEE Transactions on Visualization and Computer Graphics*, 30(1):649–660, 2024. doi: 10.1109/TVCG.2023.3327378 2, 4, 5

[8] L. Besançon, N. Peiffer-Smadja, C. Segalas, H. Jiang, P. Masuzzo, C. Smout, E. Billy, M. Deforet, and C. Leyrat. Open science saves lives: lessons from the COVID-19 pandemic. *BMC Medical Research Methodology*, 21(1):1–18, 2021. doi: 10.1186/s12874-021-01304-y 4

[9] L. Besançon, K. Schönborn, E. Sundén, H. Yin, S. Rising, P. Westerdahl, P. Ljung, J. Wideström, C. Hansen, and A. Ynnerman. Exploring and explaining climate change: Exploranation as a visualization pedagogy for societal action. In *VIS4GOOD, a workshop on Visualization for Social Good, held as part of IEEE VIS 2022*, 2022. 1, 4, 5

[10] L. Besançon, A. Semmo, D. Biau, B. Frachet, V. Pineau, E. H. Sariali, M. Soubeyrand, R. Taouachi, T. Isenberg, and P. Dragicevic. Reducing affective responses to surgical images and videos through stylization. In *Computer Graphics Forum*, vol. 39, pp. 462–483. Wiley Online Library, 2020. 4

[11] L. Besançon, A. Ynnerman, D. F. Keefe, L. Yu, and T. Isenberg. The State of the Art of Spatial Interfaces for 3D Visualization. *Computer Graphics Forum*, 40(1):293–326, Feb. 2021. doi: 10/gjbpxp 2

[12] A. Bezerianos, M. Correll, K. Hall, S. Huron, M. Kay, and M. Meyer. Beliv 2022 preface. In *2022 IEEE Workshop on Evaluation and Beyond - Methodological Approaches for Visualization (BELIV)*, pp. 8–8, 2022. doi: 10.1109/BELIV57783.2022.00017 2

[13] A. Bezerianos, K. Hall, S. Huron, M. Kay, M. Meyer, and M. Sedlmair. Beliv 2020 preface. In *2020 IEEE Workshop on Evaluation and Beyond - Methodological Approaches to Visualization (BELIV)*, pp. 7–7, 2020. doi: 10.1109/BELIV51497.2020.00005 2

[14] B. S. Bloom, M. D. Engelhart, E. Furst, W. H. Hill, and D. R. Krathwohl. Taxonomy of educational objectives: The classification of educational goals. handbook 1: Cognitive domain. *David McKay*, 1956. 2

[15] A. Bock, E. Axelsson, J. Costa, G. Payne, M. Acinapura, V. Trakinski, C. Emmart, C. Silva, C. Hansen, and A. Ynnerman. Openspace: A system for astrographics. *IEEE Transactions on Visualization and Computer Graphics*, 26(1):633–642, 2020. doi: 10.1109/TVCG.2019.2934259 1, 4

[16] A. Bock, E. Axelsson, C. Emmart, M. Kuznetsova, C. Hansen, and A. Ynnerman. Openspace: Changing the narrative of public dissemination in astronomical visualization from what to how. *IEEE Computer Graphics and Applications*, 38(3):44–57, 2018. doi: 10.1109/MCG.2018.032421653 4

[17] M. A. Borkin, Z. Bylinskii, N. W. Kim, C. M. Bainbridge, C. S. Yeh, D. Borkin, H. Pfister, and A. Oliva. Beyond memorability: Visualization recognition and recall. *IEEE Transactions on Visualization and Computer Graphics*, 22(1):519–528, 2016. doi: 10.1109/TVCG.2015.2467732 3

[18] K. Börner, A. Bueckle, and M. Ginda. Data visualization literacy: Definitions, conceptual frameworks, exercises, and assessments. *Proceedings of the National Academy of Sciences*, 116(6):1857–1864, 2019. doi: 10.1073/pnas.1807180116 4, 5

[19] M. Böttinger, H.-N. Kostis, M. Velez-Rojas, P. Rheingans, and A. Ynnerman. *Reflections on Visualization for Broad Audiences*, pp. 297–305. Springer, 2020. doi: 10.1007/978-3-030-34444-3_16 2

[20] J. Boy, R. A. Rensink, E. Bertini, and J.-D. Fekete. A principled way of assessing visualization literacy. *IEEE Transactions on Visualization and Computer Graphics*, 20(12):1963–1972, 2014. doi: 10.1109/TVCG.2014.2346984 2, 4, 5

[21] M. Brossier, R. Skånberg, L. Besançon, M. Linares, T. Isenberg, A. Ynnerman, and A. Bock. Moliverse: Contextually embedding the microcosm into the universe. *Computers & Graphics*, 112:22–30, 2023. doi: 10.1016/j.cag.2023.02.006 4

[22] A. Burns, C. Xiong, S. Franconeri, A. Cairo, and N. Mahyar. How to evaluate data visualizations across different levels of understanding. In *2020 IEEE Workshop on Evaluation and Beyond - Methodological Approaches to Visualization (BELIV)*, pp. 19–28, 2020. doi: 10.1109/BELIV51497.2020.00010 2

[2] https://ieeevis.org/year/2023/info/keynote-speaker

[23] I. Chalmers and P. Glasziou. Avoidable waste in the production and reporting of research evidence. *The Lancet*, 374(9683):86–89, 2009. doi: 10.1016/S0140-6736(09)60329-9 4

[24] P. Chandler and J. Sweller. Cognitive load theory and the format of instruction. *Cognition and Instruction*, 8(4):293–332, 1991. 3

[25] H. Chen. Collaborative systems: solving the vocabulary problem. *Computer*, 27(5):58–66, 1994. doi: 10.1109/2.291290 4

[26] L. Chittaro. Designing serious games for safety education: "learn to brace" versus traditional pictorials for aircraft passengers. *IEEE Transactions on Visualization and Computer Graphics*, 22(5):1527–1539, 2016. doi: 10.1109/TVCG.2015.2443787 2

[27] L. Chittaro and F. Buttussi. Assessing knowledge retention of an immersive serious game vs. a traditional education method in aviation safety. *IEEE Transactions on Visualization and Computer Graphics*, 21(4):529–538, 2015. doi: 10.1109/TVCG.2015.2391853 2

[28] J. J. Cohen, V. Azarova, C. A. Klöckner, A. Kollmann, E. Löfström, G. Pellegrini-Masini, J. G. Polhill, J. Reichl, and D. Salt. Tackling the challenge of interdisciplinary energy research: A research toolkit. *Energy Research & Social Science*, 74:101966, 2021. doi: 10.1016/j.erss.2021.101966 4

[29] M. Creamer, L. Padilla, and M. A. BORKIN. Finding gaps in modern visualization literacy. 2024. doi: 10.31219/osf.io/jy9v2 4

[30] E. Dimara and C. Perin. What is interaction for data visualization? *IEEE Transactions on Visualization and Computer Graphics*, 26(1):119–129, 2020. doi: 10.1109/TVCG.2019.2934283 4

[31] H. Elhamdadi, A. Gaba, Y.-S. Kim, and C. Xiong. How do we measure trust in visual data communication? In *2022 IEEE Workshop on Evaluation and Beyond - Methodological Approaches for Visualization (BELIV)*, pp. 85–92, 2022. doi: 10.1109/BELIV57783.2022.00014 2

[32] O. ElTayeby and W. Dou. A survey on interaction log analysis for evaluating exploratory visualizations. In *Proceedings of the Sixth Workshop on Beyond Time and Errors on Novel Evaluation Methods for Visualization*, BELIV '16, 8 pages, p. 62–69. Association for Computing Machinery, New York, NY, USA, 2016. doi: 10.1145/2993901.2993912 2

[33] A. Evmenova. Preparing teachers to use universal design for learning to support diverse learners. *Journal of Online Learning Research*, 4(2):147–171, 2018. 1

[34] P. Felten. Visual literacy. *Change: The magazine of higher learning*, 40(6):60–64, 2008. doi: 10.3200/CHNG.40.6.60-64 4

[35] E. E. Firat, A. Joshi, and R. S. Laramee. Interactive visualization literacy: The state-of-the-art. *Information Visualization*, 21(3):285–310, 2022. doi: 10.1177/14738716221081831 5

[36] R. B. Fransecky and J. L. Debes. Visual literacy: A way to learn–a way to teach. 1972. 4

[37] J. Fuchs, B. Jäckl, M. Jüttler, D. A. Keim, and R. Sevastjanova. Treeducation: A visual education platform for teaching treemap layout algorithms. *IEEE Transactions on Visualization and Computer Graphics*, pp. 1–16, 2024. doi: 10.1109/TVCG.2024.3393012 2

[38] B. Gregorcic and J. Haglund. Conceptual blending as an interpretive lens for student engagement with technology: Exploring celestial motion on an interactive whiteboard. *Research in Science Education*, 51(2):235–275, 2021. doi: 10.1007/s11165-018-9794-8 3

[39] L. Hakimi, R. Eynon, and V. A. Murphy. The ethics of using digital trace data in education: A thematic review of the research landscape. *Review of educational research*, 91(5):671–717, 2021. doi: 10.3102/00346543211020116 1

[40] J. Hallström, P. Norström, and K. J. Schönborn. Authentic stem education through modelling: an international delphi study. *International Journal of STEM education*, 10(1):62, 2023. doi: 10.1186/s40594-023-00453-4 1

[41] J. Hallström and K. J. Schönborn. Models and modelling for authentic stem education: Reinforcing the argument. *International Journal of STEM education*, 6(1):22, 2019. doi: 10.1186/s40594-019-0178-z 1

[42] S. He and E. Adar. Vizitcards: A card-based toolkit for infovis design education. *IEEE Transactions on Visualization and Computer Graphics*, 23(1):561–570, 2017. doi: 10.1109/TVCG.2016.2599338 2

[43] R. Heinich. *Instructional media and technologies for learning*. Merrill, 1996. 4

[44] J. Herring, M. S. VanDyke, R. G. Cummins, and F. Melton. Communicating local climate risks online through an interactive data visualization. *Environmental Communication*, 11(1):90–105, 2017. doi: 10.1080/17524032.2016.1176946 1

[45] U. Hinrichs, H. Schmidt, and S. Carpendale. Emdialog: Bringing information visualization into the museum. *IEEE Trans. Vis. Comput. Graph.*, 14:1181–1188, 2008. doi: 10.1109/TVCG.2008.127 2

[46] R. Hobbs. *Create to Learn: Introduction to Digital Literacy*. John Wiley & Sons, Hoboken, NJ, 2017. 4

[47] G. Höst, K. Palmerius, and K. Schönborn. Nano for the public: An exploranation perspective. *IEEE Computer Graphics and Applications*, 40(2):32–42, 2020. doi: 10.1109/MCG.2020.2973120 2, 4, 5

[48] J. Jarke and A. Breiter. The datafication of education. *Learning, Media and Technology*, 44(1):1–6, 2019. doi: 10.1080/17439884.2019.1573833 1

[49] D. Jia, A. Irger, L. Besancon, O. Strnad, D. Luo, J. Bjorklund, A. Ynnerman, and I. Viola. VOICE: Visual oracle for interaction, conversation, and explanation. arXiv preprint 2304.04083, 2024. doi: 10/m4ft 1

[50] D. F. Keefe. Integrating visualization and interaction research to improve scientific workflows. *IEEE Computer Graphics and Applications*, 30(2):8–13, 2010. doi: 10.1109/MCG.2010.30 4

[51] M. Koć-Januchta, T. Höffler, G. B. Thoma, H. Prechtl, and D. Leutner. Visualizers versus verbalizers: Effects of cognitive style on learning with texts and pictures–an eye-tracking study. *Computers in Human Behavior*, 68:170–179, 2017. doi: 10.1016/j.chb.2016.11.028 3

[52] M. M. Koć-Januchta, K. J. Schönborn, C. Roehrig, V. K. Chaudhri, L. A. Tibell, and H. C. Heller. "connecting concepts helps put main ideas together": cognitive load and usability in learning biology with an ai-enriched textbook. *International Journal of Educational Technology in Higher Education*, 19(1):11, 2022. doi: 10.1186/s41239-021-00317-3 3

[53] M. Krone, K. Schatz, N. Hieronymus, C. Müller, M. Becher, T. Barthelmes, A. Cooper, S. Currle, P. Gralka, M. Hlawatsch, L. Pietrzyk, T. Rau, G. Reina, R. Trefft, and T. Ertl. From visualization research to public presentation - design and realization of a scientific exhibition. In *Proc. SIGRAD*, p. 17–24, 2017. 2

[54] H. Lam, E. Bertini, P. Isenberg, C. Plaisant, and S. Carpendale. Empirical studies in information visualization: Seven scenarios. *IEEE Transactions on Visualization and Computer Graphics*, 18(9):1520–1536, 2012. doi: 10.1109/TVCG.2011.279 2

[55] G. Lampropoulos and Kinshuk. Virtual reality and gamification in education: a systematic review. *Educational technology research and development*, pp. 1–95, 2024. doi: 10.1007/s11423-024-10351-3 1

[56] J. H. Larkin and H. A. Simon. Why a diagram is (sometimes) worth ten thousand words. *Cognitive Science*, 11(1):65–100, 1987. doi: 10.1111/j.1551-6708.1987.tb00863.x 3

[57] S. Lee, S.-H. Kim, and B. C. Kwon. Vlat: Development of a visualization literacy assessment test. *IEEE transactions on visualization and computer graphics*, 23(1):551–560, 2016. doi: 10.1109/TVCG.2016.2598920 4, 5

[58] E. Lee-Robbins and E. Adar. Affective learning objectives for communicative visualizations. *IEEE Transactions on Visualization and Computer Graphics*, 29(01):1–11, jan 2023. doi: 10.1109/TVCG.2022.3209500 3

[59] S. LYi, Q. Wang, F. Lekschas, and N. Gehlenborg. Gosling: A grammar-based toolkit for scalable and interactive genomics data visualization. *IEEE Transactions on Visualization and Computer Graphics*, 28(1):140–150, 2022. doi: 10.1109/TVCG.2021.3114876 1, 4

[60] J. Ma, I. Liao, K.-L. Ma, and J. Frazier. Living liquid: Design and evaluation of an exploratory visualization tool for museum visitors. *IEEE Transactions on Visualization and Computer Graphics*, 18(12):2799–2808, 2012. doi: 10.1109/TVCG.2012.244 2

[61] J. Ma, K.-L. Ma, and J. Frazier. Decoding a complex visualization in a science museum – an empirical study. *IEEE Transactions on Visualization and Computer Graphics*, 26(1):472–481, 2020. doi: 10.1109/TVCG.2019.2934401 1, 3

[62] K.-L. Ma, I. Liao, J. Frazier, H. Hauser, and H.-N. Kostis. Scien-

tific storytelling using visualization. *IEEE Computer Graphics and Applications*, 32(1):12–19, 2012. doi: 10.1109/MCG.2012.24 5

[63] R. Maciejewski, P. Livengood, S. Rudolph, T. F. Collins, D. S. Ebert, R. T. Brigantic, C. D. Corley, G. A. Muller, and S. W. Sanders. A pandemic influenza modeling and visualization tool. *Journal of Visual Languages & Computing*, 22(4):268–278, 2011. doi: 10.1016/j.jvlc.2011.04.002 1

[64] M. Mani, M. Koc-Januchta, K. Schönborn, M. Gezelius, G. Höst, and J. Löwgren. Empirical design of a visual learning environment to support pupils' systems thinking. In *Proc. ECER Conference*. European Educational Research Association (EERA), Glasgow, Scotland, 2023. 1

[65] P. Mantri, H. Subramonyam, A. L. Michal, and C. Xiong. How do viewers synthesize conflicting information from data visualizations? *IEEE Transactions on Visualization and Computer Graphics*, 29(1):1005–1015, 2023. doi: 10.1109/TVCG.2022.3209467 3

[66] R. E. Mayer. Multimedia learning. In *Psychology of learning and motivation*, vol. 41, pp. 85–139. Elsevier, 2002. doi: 10.1016/S0079-7421(02)80005-6 1, 3

[67] R. E. Mayer. The past, present, and future of the cognitive theory of multimedia learning. *Educational Psychology Review*, 36(1):8, 2024. doi: 10.1007/s10648-023-09842-1 1, 3

[68] E. H. McKinney, S. G. Green, K. A. Heppard, and J. Wu. Improving collaboration in ambiguous settings by recognizing the importance of a common domain vocabulary: An active learning exercise. *Communications of the Association for Information Systems*, 52(1):815–832, 2023. doi: 10.17705/1CAIS.05239 4

[69] M. Meyer and J. Dykes. Criteria for rigor in visualization design study. *IEEE Transactions on Visualization and Computer Graphics*, 26(01):87–97, jan 2020. doi: 10.1109/TVCG.2019.2934539 3, 4

[70] L. E. Mnguni. The theoretical cognitive process of visualization for science education. *SpringerPlus*, 3:1–9, 2014. doi: 10.1186/2193-1801-3-184 1

[71] M. C. Monroe, R. R. Plate, A. Oxarart, A. Bowers, and W. A. Chaves. Identifying effective climate change education strategies: A systematic review of the research. *Environmental Education Research*, 25(6):791–812, 2019. doi: 10.1080/13504622.2017.1360842 5

[72] E. G. Offerdahl, J. B. Arneson, and N. Byrne. Lighten the load: Scaffolding visual literacy in biochemistry and molecular biology. *CBE—Life Sciences Education*, 16(1):es1, 2017. doi: 10.1187/cbe.16-06-0193 1

[73] K. L. Palmerius and K. J. Schönborn. Visualizing and exploring heat in a science center. In *Thermal Cameras in Science Education*, pp. 187–203. Springer, 2012. doi: 10.1007/978-3-030-85288-7_12 1

[74] D. Parmar, L. Lin, N. DSouza, S. Jörg, A. E. Leonard, S. B. Daily, and S. V. Babu. How immersion and self-avatars in vr affect learning programming and computational thinking in middle school education. *IEEE Transactions on Visualization and Computer Graphics*, 29(8):3698–3713, 2023. doi: 10.1109/TVCG.2022.3169426 2, 3

[75] K. Parti and A. Szigeti. The future of interdisciplinary research in the digital era: Obstacles and perspectives of collaboration in social and data sciences-an empirical study. *Cogent Social Sciences*, 7(1):1970880, 2021. doi: 10.1080/23311886.2021.1970880 4

[76] H. Pokojná, B. Kozlíková, D. Berry, S. Kriglstein, and K. Furmanová. Seeing the unseen: Comparison study of representation approaches for biochemical processes in education. *Plos one*, 18(11):e0293592, 2023. doi: 10.1371/journal.pone.0293592 1

[77] V. Pooryousef, M. Cordeil, L. Besançon, C. Hurter, T. Dwyer, and R. Bassed. Working with forensic practitioners to understand the opportunities and challenges for mixed-reality digital autopsy. In *Proc. CHI*, article no. 843, 15 pages. Association for Computing Machinery, New York, 2023. doi: 10.1145/3544548.3580768 1, 4

[78] P. Potvin and A. Hasni. Analysis of the decline in interest towards school science and technology from grades 5 through 11. *Journal of Science Education and Technology*, 23(6):784–802, 2014. doi: 10.1007/s10956-014-9512-x 4

[79] I. Radu and B. Schneider. How augmented reality (ar) can help and hinder collaborative learning: A study of ar in electromagnetism education. *IEEE Transactions on Visualization and Computer Graphics*, 29(9):3734–3745, 2023. doi: 10.1109/TVCG.2022.3169980 2, 3

[80] P. Rheingans, H.-N. Kostis, P. A. Oemig, G. B. Robbins, and A. Ynnerman. *Reaching Broad Audiences in an Educational Setting*, pp. 365–380. Springer, 2020. doi: 10.1007/978-3-030-34444-3_20 2

[81] C. Robson. *Real World Research*, vol. 2. Blackwell, Oxford, 2002. 3

[82] S. Samuel, C. Elvezio, S. Khan, L. Z. Bitzer, L. Moss-Salentijn, and S. Feiner. Visuo-haptic vr and ar guidance for dental nerve block education. *IEEE Transactions on Visualization and Computer Graphics*, 30(5):2839–2848, 2024. doi: 10.1109/TVCG.2024.3372125 2

[83] K. J. Schönborn and T. R. Anderson. The importance of visual literacy in the education of biochemists. *Biochemistry and molecular biology education*, 34(2):94–102, 2006. doi: 10.1002/bmb.2006.49403402094 1, 2, 4

[84] K. J. Schönborn and T. R. Anderson. Bridging the educational research-teaching practice gap: Foundations for assessing and developing biochemistry students' visual literacy. *Biochemistry and molecular biology education*, 38(5):347–354, 2010. doi: 10.1002/bmb.20436 1, 3

[85] K. J. Schönborn and S. Bögeholz. Knowledge transfer in biology and translation across external representations: Experts'views and challenges for learning. *International Journal of Science and Mathematics Education*, 7:931–955, 2009. doi: 10.1007/s10763-009-9153-3 3

[86] K. J. Schönborn, G. E. Höst, and K. E. L. Palmerius. Nano education with interactive visualization. *Nano Today*, 11(5):543–546, 2016. doi: 10.1016/j.nantod.2015.10.006 1, 3

[87] M. Schwab, H. Strobelt, J. Tompkin, C. Fredericks, C. Huff, D. Higgins, A. Strezhnev, M. Komisarchik, G. King, and H. Pfister. booc.io: An education system with hierarchical concept maps and dynamic non-linear learning plans. *IEEE Transactions on Visualization and Computer Graphics*, 23(1):571–580, 2017. doi: 10.1109/TVCG.2016.2598518 2

[88] K. J. Schönborn and T. R. Anderson. A model of factors determining students' ability to interpret external representations in biochemistry. *International Journal of Science Education*, 31(2):193–232, 2009. doi: 10.1080/09500690701670535 3

[89] K. J. Schönborn, P. Bivall, and L. A. Tibell. Exploring relationships between students' interaction and learning with a haptic virtual biomolecular model. *Computers & Education*, 57(3):2095–2105, 2011. doi: 10.1016/j.compedu.2011.05.013 3

[90] M. Sedlmair, M. Meyer, and T. Munzner. Design study methodology: Reflections from the trenches and the stacks. *IEEE Transactions on Visualization and Computer Graphics*, 18(12):2431–2440, 2012. doi: 10.1109/TVCG.2012.213 2, 3, 4

[91] F. Serafini. *Reading the Visual: An Introduction to Teaching Multimodal Literacy*. Teachers College Press, New York, NY, 2014. 4

[92] M. Sereno, X. Wang, L. Besançon, M. J. McGuffin, and T. Isenberg. Collaborative work in augmented reality: A survey. *IEEE Transactions on Visualization and Computer Graphics*, 28(6):2530–2549, 2022. doi: 10.1109/TVCG.2020.3032761 4

[93] R. Skanberg, I. Hotz, A. Ynnerman, and M. Linares. Viamd: A software for visual interactive analysis of molecular dynamics. *Journal of Chemical Information and Modeling*, 63(23):7382–7391, 2023. doi: 10.1021/acs.jcim.3c01033 1, 4

[94] S. Stokes. Visual literacy in teaching and learning: A literature perspective. *Electronic Journal for the integration of Technology in Education*, 1(1):10–19, 2002. 4

[95] D. Sun, Y. Zhan, Z. H. Wan, Y. Yang, and C.-K. Looi. Identifying the roles of technology: A systematic review of stem education in primary and secondary schools from 2015 to 2023. *Research in Science & Technological Education*, pp. 1–25, 2023. doi: 10.1080/02635143.2023.2251902 1

[96] D. A. Szafir, S. Haroz, M. Gleicher, and S. Franconeri. Four types of ensemble coding in data visualizations. *Journal of vision*, 16(5):11–11, 2016. doi: 10.1167/16.5.11 4

[97] X. Wang, L. Besançon, D. Rousseau, M. Sereno, M. Ammi, and T. Isenberg. Towards an understanding of augmented reality extensions for existing 3d data analysis tools. In *Proc. CHI*, 13 pages, p. 1–13. Association for Computing Machinery, New York, 2020. doi: 10.1145/3313831.3376657 1, 4

[98] Y. Wang, C. Jiao, M. Bâce, and A. Bulling. Visrecall: Quantifying information visualisation recallability via question answering. *IEEE Transactions on Visualization and Computer Graphics*, 28(12):4995–5005, 2022. doi: 10.1109/TVCG.2022.3198163 3

[99] R. E. Wileman. *Visual communicating*. Educational Technology, Englewood Cliffs, New Jersey, 1993. 4

[100] B. Williamson. Digital education governance: data visualization, predictive analytics, and 'real-time'policy instruments. *Journal of education policy*, 31(2):123–141, 2016. doi: 10.1080/02680939.2015.1035758 1

[101] M. Wilson. Six views of embodied cognition. *Psychonomic Bulletin & Review*, 9:625–636, 2002. doi: 10.3758/BF03196322 3

[102] A. Wu, Y. Wang, X. Shu, D. Moritz, W. Cui, H. Zhang, D. Zhang, and H. Qu. Ai4vis: Survey on artificial intelligence approaches for data visualization. *IEEE Transactions on Visualization and Computer Graphics*, 28(12):5049–5070, 2022. doi: 10.1109/TVCG.2021.3099002 1

[103] A. Ynnerman, J. Löwgren, and L. Tibell. Exploranation: A new science communication paradigm. *IEEE Computer Graphics and Applications*, 38(3):13–20, 2018. doi: 10.1109/MCG.2018.032421649 4

[104] A. Ynnerman, T. Rydell, D. Antoine, D. Hughes, A. Persson, and P. Ljung. Interactive visualization of 3D scanned mummies at public venues. *ACM*, 59:72–81, 2016. doi: 10.1145/2950040 2

[105] P. Yu, A. Nordman, M. Koc-Januchta, K. Schönborn, L. Besançon, and K. Vrotsou. Revealing interaction dynamics: Multi-level visual exploration of user strategies with an interactive digital environment. *IEEE Transactions on Visualization and Computer Graphics*, 1, To appear. doi: 10.31219/osf.io/4yc8s 2, 5

[106] C. Ziemkiewicz, M. Chen, D. H. Laidlaw, B. Preim, and D. Weiskopf. Open challenges in empirical visualization research. In *Foundations of Data Visualization*, pp. 243–252. Springer, 2020. doi: 10.1007/978-3-030-34444-3_12 3