

# Making Data Harder to Read: Visualizations that Intentionally Increase Time and Effort

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## ABSTRACT

This position paper questions the common prioritization of data visualization designs that minimize the time and effort required from viewers, particularly in the context of communicative visualizations. Our argument is grounded in observations of designs that deliberately increase reading time and physical effort. While decreasing efficiency, it enhances other communication purposes. We illustrate such approaches with three examples focused on communicating environmental issues. We then argue that this kind of design deserves more attention in the visualization community and conclude with future research opportunities.

**Index Terms:** data visualization, effort, time, data-driven experience

## 1 INTRODUCTION

The objectives of data visualization designs have been expanded beyond presenting data in the most cognitively efficient way to broader communicative purposes, such as facilitating knowledge acquisition, evoking affective responses, and persuasion [1, 20, 26, 6]. However, ongoing debates highlight a tension between achieving broader communicative goals and prioritizing efficiency in data visualization. For example, Hullman et al. [13] discussed how introducing visual difficulties in information visualization can facilitate active processing and increase user engagement, ultimately enhancing comprehension and information recall. Correll and Gleicher [8] presented data visualization cases where distorting or obscuring data creates better outcomes in terms of knowledge acquisition and decision-making. Bertini et al. [2] argued that following visual channel rankings of perceptual effectiveness (e.g., using position over color for quantitative data) does not sufficiently account for the effectiveness of varied perceptual tasks, nor does it fully capture a chart's utility in communicating data, or the broader role and impact of visualizations.

This paper argues for more research attention to visualization designs that intentionally increase the time and physical effort in proportion to larger data values. By “intentionally,” we mean that it differs from cases where increased time and effort are trade-offs or side effects made to boost user engagement or comprehension, such as the inclusion of extraneous graphical elements (e.g., chart junk) and gamification [13]. It is also distinct from visualizations that require more time because they provide richer contextual information or insights. In contrast, the design approach this paper discusses purposefully seeks to: 1) encourage deeper thinking and reflection by increasing the time needed to read, and 2) help viewers connect the time and effort they invest in understanding the visualization with the magnitude and severity of the issue behind the data.

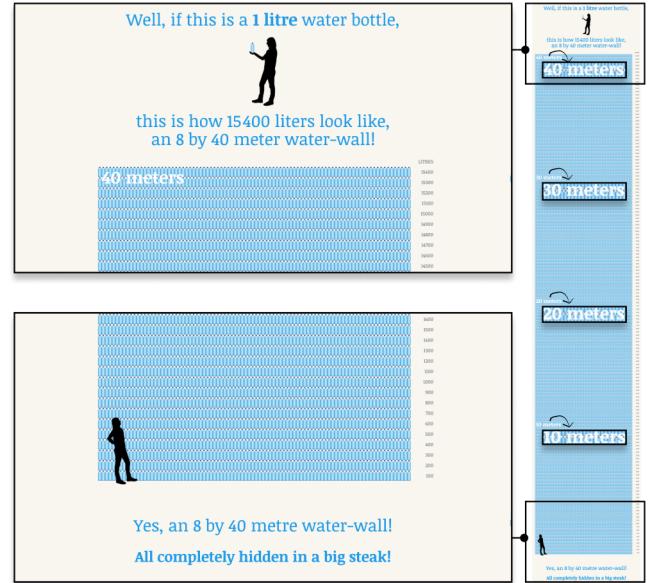


Figure 1: The screenshots from “What If I told You: You Eat 3496 Litres of Water” by InfoDesignLab [15]. The left part includes screenshots without zooming the viewport, and the right part is the overview of the visualization visible after zooming out.

Next, we will illustrate the design approach through three examples. We then discuss new perspectives and research opportunities the design approach brings.

## 2 EXAMPLES

This section introduces three examples that intentionally demand reading time and physical effort from viewers, including two online articles that apply data scrolltelling (“stories unfold as the reader scrolls” [24]) and one data physicalization. These examples resemble conventional data visualizations, but rather than ensuring the entire visualization is displayed at a user-friendly, easily readable scale, they enlarge the visualization or conceal parts of it, and require users to spend additional time and interaction effort to access the full content. They are good starting points for explaining how time and effort can be leveraged, serving as baseline cases from which more complex manipulations can be explored. We discuss that the design space for deliberately increasing reading time and physical effort can be much broader in Section 4.3.

### 2.1 What If I Told You: You Eat 3496 Litres of Water

“What If I Told You: You Eat 3496 Litres of Water” explains daily water consumption, including not only water used for domestic purposes (e.g., drinking, cooking, and washing), but also the water required to produce the industrial products and food we consume every day [15]. According to this visualization, on average, a person consumes 15,400 liters of water daily. The article concludes with a visualization that shows how many 1-liter water bottles are needed

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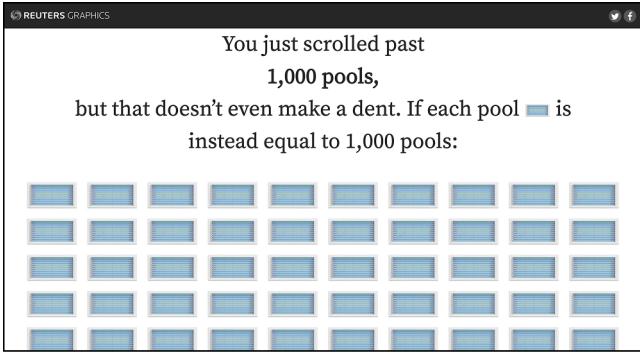


Figure 2: A screenshot of the online article “Sea Level Rise by the Numbers” from *Reuters* [7].

to represent 15,400 liters, by stacking the bottles into a wall. Readers need to scroll the equivalent of six screen heights to fully view the visualization (Figure 2).

## 2.2 Sea Level Rise by the Numbers

Between 2002 and 2017, Greenland lost an average of 286 gigatonnes of ice mass per year, equivalent to 75.6 trillion gallons of water. The online article “Sea Level Rise by the Numbers” illustrates this by showing it would take 114.4 million Olympic-sized swimming pools to contain that volume. The article does not reveal the number directly, but it invites readers to scroll through rows of pools to discover it themselves. After 100 rows, readers learn that they have seen 1,000 pools, which is far from the full amount (Figure 2). Readers are asked to scroll again, this time to see how many pools are required if each represents 1,000 pools. After 100 rows, readers learn that they reach 1 million pools, yet the goal remains distant. Finally, it is visualized how many pools are required if each represents 1 million pools. Only then can readers view the whole visualization without extensive scrolling.

## 2.3 Du Papier Toilette (Oui Oui...) (Toilet Paper (Yes Yes...))

This is a performative visualization that uses toilet paper to represent the size in KB of different digital media, with one sheet representing 60MB [25]. It reflects on the environmental impacts of digital technology by calling attention to the rebound effect. The message relates to that we are asking for ever higher resolution (4K, HDR etc.), more and more resources are needed. The presenter asked the audience how many sheets of paper would be needed for different media consumption, and the presenter unrolled the paper to give the answer. For instance, 1 hour of HD video on Netflix equals 50 sheets (3GB). To know the answer, the audience waited and helped hold unrolled sheets.

## 3 SIMILAR DESIGNS IN RELATED WORK

This paper is not the first to discuss visualization designs like those presented in the examples above. In particular, we identify two related works that our arguments intersect. Lan et al. [18] investigated design strategies for evoking negative emotions in serious data stories and included the first two examples in their corpus, labeled as using the design method *stretched layout*, “which deliberately increases the length of a visualization so that viewers have to scroll for a while to view it completely.” Solen and Munzner [23] proposed a design space for visualizations in which the smallest and largest items differ significantly in size. Although the examples we examine do not fall within the type of visualizations targeted by their design space, a related strategy they describe, *Lengthy Pan*, shares design similarities: “a visualization design that involves only

a single total scale that the user pans along and which relies on visceral time.” In this context, “panning” refers to not only the screen-based interaction but also users physically moving in the real world to explore a visualization. Although both papers acknowledged the use of reading time manipulation as a design strategy for different ends, they did not explore this aspect in depth, as their scope encompassed broader themes. We argue that this strategy merits more research, and that there is more to be investigated in terms of why and how to incorporate time and effort into data visualizations.

## 4 NEW PERSPECTIVES AND OPPORTUNITIES IN DATA VISUALIZATION RESEARCH

### 4.1 Simple Data May Take More Effort to Communicate

The data in the three examples could have been represented simply as numbers or through user-friendly, adequately-scaled visualizations. Instead, the creators chose approaches that require more effort—both from the viewer, and (likely) from the designer. This choice prompts us to reflect on a dominant mindset in the visualization community: that communicating large-scale, complex data is inherently more challenging and therefore more worthy of effort and research [9]. However, we argue that communicating simple data in a meaningful way presents its distinct challenges. When data is straightforward, a minimal or overly simple presentation can lead viewers to feel they have grasped the message instantly. As a result, they may disengage quickly, believing there is nothing more to explore or reflect on. This issue is compounded by the broader challenge facing public media today. That is, people are increasingly affected by short attention spans and information overload. They allocate less time to consuming information and frequently switch topics. We argue that designing visualizations of simple data, which invite deeper engagement, is a challenge that deserves more recognition and research.

### 4.2 New Data Communication Channels

Time and physical effort can be regarded as new data communication channels. Data visualization researchers have long explored how to move beyond purely visual representations, incorporating additional sensory modalities such as haptics [16], audio [17], olfaction [22], and even visceral feelings [19]. These alternative channels are used not merely for accessibility, but to evoke richer and more embodied understandings of data [10]. Similarly, time and physical effort can shape how data is perceived and interpreted. Rather than serving purely as barriers to be minimized, time and effort can be designed as communicative signals, inviting the viewer to feel the weight or urgency of the data and the issues behind it. Thus, we argue that they are promising communication channels in the design of affective and impactful data experiences.

### 4.3 A Vast Design Space to Be Explored

The three examples are all variations around scrolling-based interactions. However, there are more potential approaches to using time and physical effort for data comprehension. For instance, prior research has explored whether requiring users to invest time and physical effort can increase their awareness of environmental issues or even influence behavior. Hurtienne et al. [14] developed an interactive device in which users were invited to generate the energy equivalent of a single Google search by pedaling a stationary bike. Similarly, Hsu et al. [12] studied virtual reality experiences where subjects are asked to repeatedly use a 600-milliliter bottle to fill a water tank for flushing a toilet or taking a shower [12]. Meanwhile, Chauvergne et al. [4] suggested that having people carry weights matching their carbon emissions could have educational value. Data visualization research also identified the benefits of embodied interactions for learning data visualizations. For example, Chen et al. [5] found that asking students to move in the physical space to mimic the positions of data points with different projection techniques can

provide sufficient engagement in learning. These explorations illustrate the variety of ways interactive systems can invite users to invest time and physical effort through different forms of physical interactions, such as cycling, repeated manual movements, and locomotion. Alternatively, interactive systems could be manipulating reading time only, such as animating a large-scale data visualization or slowing the animation speed. To sum up, we argue that there is a potentially large design space for how visualizations can meaningfully incorporate time and effort into the user experience.

#### 4.4 Studying the Effects of Time and Effort

This topic raises many research questions. At the most basic level, does increasing reading time and physical effort help achieve design goals such as increasing data comprehension? Designing and implementing studies to understand the effects of intentionally increasing data visualization reading time and physical effort is challenging. The first challenge is setting the study conditions. Generating different levels of reading time and physical efforts is hard to control because they vary between individuals. A possible solution is to find or create a set of visualizations that fall into different ranges of reading time and effort. This requires lots of pilot studies to figure out which ranges are meaningful and how to design for them. It may also require using advanced tools, such as wearable monitors [3] and physiological sensors [11] to track the effort users make depending on the questions to be studied. Another challenge lies in designing appropriate tasks and evaluation measures. Unlike measuring task accuracy and response time, it is more difficult to assess the abstract outcomes that this type of visualization design aims to achieve, like user engagement, affective impact, attitudinal change, or interpretive depth. This is especially challenging in lab or crowdsourcing-based studies, where participants may either try harder than they naturally would [21] or rush through tasks without real engagement.

#### 5 WHEN THE DESIGN CAN GO INEFFECTIVE

We acknowledge that increasing time and physical effort does not always lead to positive outcomes and can, in fact, result in negative effects. We discuss two major limitations. Whether and how these drawbacks can be effectively addressed remains an open research question.

**It may lead to an imprecise understanding of data.** Compared with conventional data visualization, the design approach in the examples is inherently less effective for perceptual tasks with data visualizations such as extracting data values. Designers and researchers should acknowledge this limitation and avoid relying on such designs when a precise perception of data is prioritized.

**It may elicit resistance or cause users to disengage.** The solution that intentionally increases reading time to avoid fast-reading habits developed by people to deal with short attention span and information overload may, in turn, fail for the same motivation: people want to save time and be efficient in consuming information. When people are asked to put too much effort into reading a visualization without any form of reward—such as an engaging narrative—they may ultimately disengage or even develop resistance to the message. It is even possible that people consider this approach poorly designed and ineffective. Therefore, this approach may not be suitable for all types of datasets, especially those that are already difficult to interpret, such as datasets with many interrelated variables.

#### 6 CONCLUSION

In this position paper, we call for research attention to data visualization designs that intentionally increase reading time and effort. We argued for research effort in enhancing the communication of simple data, considering time and effort as new data communica-

tion channels, and future studies of design methods that leverage time and effort to communicate data.

#### ACKNOWLEDGMENTS

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#### REFERENCES

- [1] E. Adar and E. Lee. Communicative visualizations as a learning problem. *IEEE Transactions on Visualization and Computer Graphics*, 27(2):946–956, 2020. [1](#)
- [2] E. Bertini, M. Correll, and S. Franconeri. Why shouldn't all charts be scatter plots? beyond precision-driven visualizations. In *Proceedings of the 2020 IEEE Visualization Conference*, pp. 206–210. IEEE, 2020. [1](#)
- [3] N. F. Butte, U. Ekelund, and K. R. Westerterp. Assessing physical activity using wearable monitors: measures of physical activity. *Medicine and Science in Sports and Exercise*, 44(1 Suppl 1):S5–S12, 2012. [3](#)
- [4] E. Chauvergne, A. Ferron, and P. Dragicevic. The weight of our decisions: Encoding carbon impact with physical load. In *Conférence Internationale Francophone sur l'Interaction Humain-Machine*, 2024. [2](#)
- [5] X. Chen, J. Z. Self, L. House, J. Wenskovitch, M. Sun, N. Wycoff, J. R. Evia, and C. North. Be the data: Embodied visual analytics. *IEEE Transactions on Learning Technologies*, 11(1):81–95, 2017. [2](#)
- [6] C. H. Chih and D. S. Parker. The persuasive phase of visualization. In *Proceedings of the 2008 ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, pp. 884–892, 2008. [1](#)
- [7] C. Christine and S. Ashlyn. Sea level rise by the numbers. <https://www.reuters.com/graphics/CLIMATECHANGE-GREENLAND-SEALEVELS/010080F60WR/>. Accessed: 2025-07-13. [2](#)
- [8] M. Correll and M. Gleicher. Bad for data, good for the brain : Knowledge-first axioms for visualization design. In G. Ellis, ed., *DECISIVe : Workshop on Dealing with Cognitive Biases in Visualisations*, 2014. [1](#)
- [9] P. Dragicevic. *Small Data - Visualizing Simple Datasets for Communication and Decision Making*. Habilitation à diriger des recherches, Université de Bordeaux, June 2023. [2](#)
- [10] T. Hogan and E. Hornecker. Towards a design space for multisensory data representation. *Interacting with Computers*, 29(2):147–167, 2017. [2](#)
- [11] J.-H. Hong, J. Ramos, and A. K. Dey. Understanding physiological responses to stressors during physical activity. In *Proceedings of the 2012 ACM Conference on Ubiquitous Computing*, pp. 270–279, 2012. [3](#)
- [12] W.-C. Hsu, C.-M. Tseng, and S.-C. Kang. Using exaggerated feedback in a virtual reality environment to enhance behavior intention of water-conservation. *Journal of Educational Technology & Society*, 21(4):187–203, 2018. [2](#)
- [13] J. Hullman, E. Adar, and P. Shah. Benefiting infovis with visual difficulties. *IEEE Transactions on Visualization and Computer Graphics*, 17(12):2213–2222, 2011. [1](#)
- [14] J. Hurtienne, F. Maas, A. Carolus, D. Reinhardt, C. Baur, and C. Wienrich. Move&find: The value of kinaesthetic experience in a casual data representation. *IEEE Computer Graphics and Applications*, 40(6):61–75, 2020. [2](#)
- [15] InfoDesignLab. What if i told you: You eat 3496 litres of water. <https://thewaterweeat.com/>. Accessed: 2025-07-13. [1](#)
- [16] Y. Jansen, P. Dragicevic, P. Isenberg, J. Alexander, A. Karnik, J. Kildal, S. Subramanian, and K. Hornbæk. Opportunities and challenges for data physicalization. In *Proceedings of the 2015 CHI Conference on Human Factors in Computing Systems*, pp. 3227–3236, 2015. [2](#)
- [17] H. G. Kaper, E. Wiebel, and S. Tipei. Data sonification and sound visualization. *Computing in Science & Engineering*, 1(4):48–58, 1999. [2](#)
- [18] X. Lan, Y. Wu, Y. Shi, Q. Chen, and N. Cao. Negative emotions, positive outcomes? exploring the communication of negativity in serious

- data stories. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems*, pp. 1–14, 2022. 2
- [19] B. Lee, D. Brown, B. Lee, C. Hurter, S. Drucker, and T. Dwyer. Data visceralization: Enabling deeper understanding of data using virtual reality. *IEEE Transactions on Visualization and Computer Graphics*, 27(2):1095–1105, 2020. 2
- [20] E. Lee-Robbins and E. Adar. Affective learning objectives for communicative visualizations. *IEEE Transactions on Visualization and Computer Graphics*, 29(1):1–11, 2022. 1
- [21] A. L. Nichols and J. K. Maner. The good-subject effect: Investigating participant demand characteristics. *The Journal of General Psychology*, 135(2):151–166, 2008. 3
- [22] B. Patnaik, A. Batch, and N. Elmquist. Information olfaction: Harnessing scent to convey data. *IEEE Transactions on Visualization and Computer Graphics*, 25(1):726–736, 2018. 2
- [23] M. Solen and T. Munzner. A design space for visualization with large scale-item ratios. *arXiv preprint arXiv:2404.01485*, 2024. 2
- [24] C. D. Stolper, B. Lee, N. Henry Riche, and J. Stasko. Emerging and recurring data-driven storytelling techniques: Analysis of a curated collection of recent stories. Technical Report MSR-TR-2016-14, April 2016. 1
- [25] T. Thibault. Du papier toilette (oui oui...). <https://thewaterweeat.com/>. Accessed: 2025-07-13. 2
- [26] F. B. Viegas and M. Wattenberg. Communication-minded visualization: A call to action. *IBM Systems Journal*, 45(4):801, 2006. 1