

Visualization Literacy or Skillset? Beyond the Analogy to Textual Literacy

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ABSTRACT

Visualization literacy, previously called graphicacy, relies on an analogy to textual literacy to communicate its intended meaning as the *ability* to use visualizations. However, there are two issues with this analogy: a mismatch where analysis contexts do not have an analogous place in textual literacy and an inherited dichotomy of literate vs. illiterate which does not accurately represent the spectrum of visualization skill. In this paper, we discuss existing literature and how it typically describes visualization literacy and the connection to textual literacy. We then propose new terminology, the *visualization skillset*, to provide more flexibility when discussing this ability and its spectrum of proficiency, and to provoke discussion on how to improve on the issues we identified. Finally, we discuss how to move forward as a field and propose directions for future work.

Index Terms: Visualization literacy, visualization skillset.

1 INTRODUCTION

The ability to use visualizations has been of concern to academic researchers for nearly a century, since educational psychologists first began assessing school-age children’s ability to learn from a variety of chart types in 1927 [38]. Similar studies assessing this ability, although without a definitive name, continued to be conducted until 1966, when Balchin and Coleman coined the term *graphicacy*, as a portmanteau of the words *graphical* and *literacy*, to refer to the ability to communicate and understand data-based relationships using visual aids [3]. In their paper, Balchin and Coleman describe graphicacy as a crucial intellectual skill that goes beyond numeracy and literacy and which must be taught early on in the educational system. This term, as well as others such as *graph comprehension*, were adopted in the following years, and are still in use in research now [34, 10, 12].

In 2014, Boy et al. proposed the term *visualization literacy* to describe people’s ability to use visualization. They mentioned other terms, including graphicacy, and argued that these terms are ambiguous and do not always refer to the ability to use visualizations. In their paper, they provided a definition for their new term: “the ability to confidently use a given data visualization to translate questions specified in the data domain into visual queries in the visual domain, as well as interpreting visual patterns in the visual domain as properties in the data domain” [7]. This term gradually

gained popularity, with some following papers using the original definition [5, 15, 16, 17] and others proposing alternatives [35].

Over the past two decades, *visualization literacy* has become the primary term for this ability. Like *graphicacy*, it uses an analogy to textual literacy to evoke the idea of it being an ability or skill. While the analogy is made simply by referring to textual literacy in these terms, existing literature often makes it even more explicit by discussing the connection to textual literacy in a sentence or even an entire paper section.

However, through reflective synthesis we have found that there are two issues with this analogy given a modern understanding of this ability, and that these issues influence and restrict the way we study this ability. First, there is a mismatch in that analysis contexts do not have a place in the literacy analogy, despite these contexts being commonly studied and becoming more common amongst the general population as data and visualization tools become more accessible. We define analysis contexts as those where the goal is to glean new insights from a dataset, whereas communication contexts are those where the goal is to communicate known, previously-gleaned insights to others. Second, visualization literacy inherits the dichotomy of literate vs. illiterate which does not reflect the diversity of ability to use visualization. In this paper, we first describe existing literature and the way it tends to discuss visualization literacy and the analogy to textual literacy. Then, we explain these two issues, discuss the potential issues that arise from these problems, and propose the *visualization skillset* as new, more accurate terminology and to provoke discussion on how we can further improve the field. We also discuss the path forward and how future work can help to better understand this skillset and fill gaps left by existing literature.

2 RELATED WORK

A significant portion of visualization literacy work focuses on assessments, both their creation and application. Boy et al.’s 2014 paper proposed a method for assessing visualization literacy as a foundation to build on as the field grew [7]. Lee et al. then developed a concrete assessment, named the Visualization Literacy Assessment Test or VLAT, and showed evidence of its validity [23]. Of the assessments developed post-VLAT, some of them explicitly note that their question or chart choices were based on or inspired by VLAT [18, 19, 27].

When assessing populations’ visualization literacy in research studies, researchers often choose to use VLAT [4, 24, 26, 30]. Some developed their own novel assessments, particularly if they were either targeting very specific visualization skills such as the ability to use treemaps [14] or they wanted to assess skills that were not assessed by VLAT such as the ability to decode unfamiliar visualizations [31]. Existing literature typically applies these assessments in formal-education contexts such as universities [14, 30, 31] and informal-education contexts such as museums [6], however some use these assessments for crowd-sourced populations [7, 24, 26] and for large language models [4]. Another component of visualization literacy work which often involves the application of these

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Citation	Definition
Boy et al., 2014 [7]	the ability to confidently use a given data visualization to translate questions specified in the data domain into visual queries in the visual domain, as well as interpreting visual patterns in the visual domain as properties in the data domain
Börner et al., 2015 [6]	the ability to make meaning from and interpret patterns, trends, and correlations in visual representations of data
Lee et al., 2016 [23]	the ability and skill to read and interpret visually represented data in and to extract information from data visualizations
Alper et al., 2017, [1]	the ability to confidently create and interpret visual representations of data
Firat et a., 2020 [14]	the ability to read, interpret, and understand the information presented in graphical designs
Huynh et al., 2020 [21]	the ability to understand and appropriately handle data visualizations
Peppler et al., 2021 [28]	the ability to read and construct visual representations to make meaning of data and to support the understanding of datasets through data visualization types
Bae et al., 2022 [2]	the ability to constructively reason with data
Solen et al., 2022 [35]	the ability to critically interpret and construct visualizations
Pozdniakov et al., 2023 [30]	the ability to read and interpret visual representations of data; and extract, process and make conclusions based on the information from such visualisations
Pandey et al., 2023 [27]	the ability to read and interpret visually represented data
Nobre et al., 2024 [26]	the ability to understand data presented in graphical elements, such as charts, graphs, and maps
Ge et al., 2025 [19]	the ability to both interpret and construct visualizations

Table 1: 13 different definitions for visualization proposed by different authors since Boy et al. proposed the term in 2014.

assessments is work which focuses on improving visualization literacy in a given population, for example by developing educational tools and games [1, 2, 17, 21] or assessing how design features cultivate visualization literacy [28].

VLAT and VLAT-based assessments are likely popular due to their generalizability, as they are used in many different contexts from school courses, to large-scale evaluations of crowd-sourced populations, to pre-study screenings. This generalizability comes from the basic level of the questions. VLAT relies on simple tasks, from the retrieval of values to the comparison of two values and the identification of trends. It also relies on familiar chart types, such as bar charts, scatterplots, and choropleth maps. These aspects of the assessment come from choices made in its development. First, Lee et al. chose to find visualization types from K-12 curriculums, authoring tools, and news outlets, leading to a set of visualization types that are commonly taught and popular in real-world use, making them familiar to most intended users. The authors chose these visualization types because, as they state in the paper, they expected test takers to be non-experts, to have learned basic visualization reading skills in school, and to have used visualization in everyday life. Second, they selected only low-level tasks from existing task taxonomies rather than higher-level tasks that may rely on multiple low-level tasks at once. They also focused their task choices on reading and interpreting, and so excluded tasks that involved construction of charts [23].

Interestingly, many of these papers also discuss the definitions and fundamental analogy of visualization literacy. Table 1 shows unique definitions for visualization literacy provided by authors since the term’s introduction. Lee et al. [23], Börner et al. [6], and Boy et al. [7] all proposed definitions for visualization literacy that are used in later papers, but it is also common for other papers to use altered forms of these definitions or to make their own definitions entirely. Most definitions focus on the interpretation of visualization, which they use a variety of words and phrases for such

as read, make meaning from, extract information from, understand, and handle, but some include other aspects of visualization such as constructing visualizations or critically analyzing visualization design choices [35]. When definitions include these components, they often use separate words for each component, for example by using both “interpret” and “construct” rather than using a common, more general word such as “use” as we do in this paper. Some of the definitions are long, explicitly mentioning specific aspects of visualization such as translating data domain questions to visual queries [7] or making conclusions based on information presented in visualizations [30]. Other long definitions are extended by the use of synonyms such as both charts and graphs [26] or both read and interpret [14, 23, 27, 30]. Meanwhile, shorter definitions tend to be less specific and allow for more flexibility [1, 2, 19, 21, 27, 35]. Finally, the definition used tends to be chosen based on the context of the work. For example, instilling confidence in the use of visualization may be particularly important in an elementary school context where students may not have been exposed to visualization before [1], and investigating the ability to understand a variety of visualization types may be more important to those studying how museum-goers view visualizations [28].

Some papers explicitly discuss the analogy to textual literacy, which is typically defined as *the ability to read and write* in visualization literacy literature [7]. They connect the two concepts with varying amounts of discussion, from single sentence connections to full paper sections [5, 7, 11, 15, 16, 19, 23, 35]. The existing analyses of this analogy focus on two clear connections: the analogy between reading text and interpreting visualizations, and the analogy between writing text and constructing visualizations. The first of these connections has been heavily referred to in the past, as a significant portion of visualization literacy work focuses only on the interpretation of visualizations. Boy et al. discuss different levels of comprehension in textual literacy, from finding information in text to making inferences and drawing on personal knowledge, and they

connect these with comparable levels of visualization comprehension [7]. The connection between writing text and constructing visualizations has also been noted in research, although much less frequently. Beyond these fundamental connections, visualization research and design often borrows linguistic terms such as metaphors [13] and analogies [33]. Even more common in existing literature is the discussion of other related skills that use the analogy to textual literacy in similar ways, such as numeracy, visual literacy, or data literacy, which are often noted as relevant skills for visualization users [5, 7, 11, 15, 16, 23, 24, 26, 28, 30].

Despite how common it is to discuss the textual literacy analogy or other related skills, no previous work discusses issues with the analogy.

3 ISSUES WITH THE ANALOGY

We describe the two issues with the analogy to literacy: the lack of an analogy for analysis and the implied dichotomy of literate vs. illiterate, then discuss their impact on the field.

3.1 A Missing Piece: Analysis

As described in Section 2, the ability to use visualization has some natural connections to textual literacy, primarily those from reading to interpreting and writing to construction. However, the reading and writing of text is typically associated with the communication of information; someone holds some knowledge, they write it down, and someone else reads it to learn that knowledge. There are analogous uses of visualization for these uses of text; someone wants to share an idea, they create a visualization that represents that idea, and someone else interprets that visualization to understand the idea. These uses of visualization are similarly tied to communication contexts, which differ from analysis contexts, which involve gleaning new information from a dataset.

Visualization analysis contexts do not have an analogous component in textual literacy. The analysis of text itself is analogous to analyzing visualization design, rather than the use of visualization to analyze a dataset. Analysis of text, where one assesses the writing choices of an author, is an activity that focuses on the analysis of the artifact used to represent the underlying information rather than on the underlying information. As writing text in textual literacy is analogous to constructing visualizations in visualization literacy, the analogous component of analyzing text is analyzing construction or design choices made by the author of the visualization.

There are additional uses of text to consider as well. A person may choose to use writing as a tool for self reflection or to clarify ideas that they are pondering. However, these uses of text are analogous to similar uses of visualization where the designer already has a clear idea of the insights or information they are visualizing and is using visualization for self reflection or to clarify their ideas. In these cases, the designer is *not* using visualization as an analysis tool as they are not using visualization to gain insights from an unfamiliar dataset. While datasets *are* designed by people, it is only the format of the dataset that must be constructed; the data itself can be completely unknown, within the parameters of its format, to any individual. Meanwhile, the information that is included in text must be fully known to those who wrote it, otherwise it would not be possible to write.

These contexts of analysis and communication exist at a high level, above the specific tasks involved, but the visualizations created for them and how they are used can differ significantly [22]. Tasks described in existing task taxonomies are sometimes specific to one of these contexts, such as Brehmer and Munzner's *present* task being tied to communication, but some are shared between these contexts, such as their *discover* task which is used both by data analysts in analysis contexts and those reading visualizations in communication contexts [8]. Visualizations made for these two

contexts tend to differ in dataset complexity and source, level of user domain knowledge, and visual complexity. Despite these differences and how common analysis is in visualization usage, the historical focus of visualization literacy on communication contexts leads to most visualization literacy work neglecting skills associated with analysis contexts.

In the visualization context typically called communication or presentation, it is logical to split the tasks of constructing the visualization and interpreting it, since they are done by different people. The designer will typically know what information they want to communicate, and their challenge lies in constructing a design which viewers will be able to unambiguously interpret in the way the designer intended. The designer may not have a fitting dataset to begin with, and may need to curate one [36]. Viewers of these visualizations may be a diverse group with varying interests, domain knowledge, and visualization abilities, so designers may choose to incorporate additional explanatory or clarifying elements into the visualization. Viewers may not be actively seeking out the information, so designers must consider engagement, and may choose to incorporate additional elements into the visualization such as visual embellishments [22]. Viewers then interpret the visualization, attempting to understand the communicated information.

Not all visualization contexts map neatly back to uses of text, however, as analysis does not have a clear text analogy. When conducting analysis, construction and interpretation can be done by the same person or team, and if there are separate design and analysis teams, the analysis team is typically involved in the design process to ensure designs meet analysis needs. The information resulting from analysis, often called insights, may not be known to anyone prior to analyzing the data, so the challenge lies in constructing a visualization that reveals these insights, either by answering specific analysis questions or enabling exploration of the dataset. This dataset must exist before the insights by definition. Analysts typically have some level of motivation to conduct analysis, for example out of personal interest or professional necessity, and most will have some domain knowledge, so designing for engagement or explanation is not necessary. Finally, interpretation tasks will either be more open ended or analyst-guided, rather than having a targeted interpretation chosen by a separate designer, as the analysts or analysis needs are considered early on.

3.2 An Inherited Dichotomy: Literate vs. Illiterate

The analogy to textual literacy provides two terms to describe people with regards to their ability: literate and illiterate. These words imply a dichotomy, where one either has the ability or not. The dichotomization of textual literacy, a skill which is better represented by a proficiency spectrum, necessitates a boundary, where all those who fall to one side of the boundary are categorized similarly. Since basic skills are likely more measurable and assessments can likely be more generalizable and stable than for more complex skills [29], this boundary is typically placed towards the lower-skilled end of the spectrum where it can separate those who have basic skills from those who do not. Naturally, this boundary placement leads to all those who have these basic skills, even those who also have higher-level skills, being classified as literate without further granularity.

However, textual literacy experts have long known that the ability is too complex for a binary classification. Instead, many researchers have proposed models that provide finer granularity for textual literacy. For example, Wagner provides the four levels of non-literate, low literate, moderate literate, and high literate [37], while Powell provides five levels: illiteracy, preliteracy, basic literacy, career literacy, and literacy [29]. Similar models exist specifically for reading, such as Herber's reading comprehension model with five levels [20], and are typically applied to educational settings. While these models still exhibit some of the problems of the

dichotomy, such as the necessitated boundary between categories, they provide more granularity than a dichotomy while remaining easy to understand. Despite this understanding, modern analyses of textual literacy amongst a given population continue to dichotomize into literate and illiterate, a simplification which may be considered necessary due to limitations in assessment during data collection [32].

Visualization literacy shares this issue of the dichotomy and a bias towards fundamental skills. While it is not a mismatch, meaning that it is an accurate part of the analogy to textual literacy, it is an inherited aspect that restricts research in the area. This inherited oversimplification has led assessments, such as the popular VLAT, to typically focus on whether those who take them have fundamental skills, such as reading off single values, comparing values, and identifying trends, on common chart types, such as bar charts, scatterplots, and choropleth maps [23]. This bias leads most visualization literacy assessments to have low discriminability amongst all who hold these fundamental skills.

However, it would be much more beneficial to stop thinking of visualization skill as binary and to understand it with finer granularity. Visualizations are used by a diverse population in a variety of ways, from social media users engaging with infographics to professional data scientists conducting data analysis, and these users all have varying visualization skill levels that cannot be easily separated into a small number of categories. Having skill-level models and assessments and using these assessments to understand where certain populations are in these models supports anyone educating about or creating visualizations. Teachers who know the skill levels of their students can prepare better and more targeted exercises, journalists who know the skill levels of their readers can make more consistent and informative designs, and even visualization researchers who know the skill levels of their users can know how novel and complex they can make their systems. While it may be beneficial to develop fine-grained bins of proficiency, we must acknowledge that this skill exists along a continuous spectrum.

3.3 Impact of the Issues

These two issues lead to visualization literacy work focusing on the use of visualization for communication, particularly whether people can read visualizations made to communicate information, and being biased towards fundamental skill levels, rather than more advanced skill levels. We are concerned that these issues have led to a categorization of visualization users into experts who can conduct analysis, who have advanced visualization skills, and for whom we do not need to consider visualization literacy, and novices who must simply be able to correctly interpret visualizations made by experts. These observations align with existing work analyzing the use of the terms novice, non-expert, layperson, and general public, which sometimes describe these individuals as lacking and who are typically defined, either explicitly or implicitly, as people who are not in proximity to science [9]. We believe that this categorization is unhelpful, as the use of visualization is much more complex, and that it leads to gaps in existing work.

Existing work has discussed another known issue with visualization literacy; it is not simply one skill, but many skills masquerading as one [27]. While being able to read charts is a commonly-discussed component of visualization literacy, visualization use also involves the design and implementation of visualizations and the critical evaluation of visualizations [35]. While recent work has begun to investigate these aspects of the skill [18, 19], they remain understudied. This issue of a multifaceted skill being modeled and assessed along a single axis is also one which exists in textual literacy, as is evident from the various models proposed for textual literacy [29, 37] and modern studies on textual literacy [32], despite efforts to construct multifaceted models for literacy such as the five critical components of reading [25]. Similar to the inherited

dichotomy, we are not arguing that this issue is a mismatch with the analogy, but rather that by inheriting it from textual literacy restricts research in the field.

4 MOVING FORWARD

We propose a new term to describe this topic: the visualization skillset. This term forgoes the analogy to literacy to avoid the previously-described issues. It uses the word *skill* to promote the idea that the ability to use visualization is not binary but rather a spectrum, so that we can more easily talk about different skill levels with much more granularity than the previous dichotomy provided. It also uses the word *set* to promote the idea that visualization use involves many skills, so that we are reminded to consider which skills are most relevant for our models, assessments, and populations. Together, we hope that the word *skillset* promotes the conceptualization of this idea as multifaceted, continuous, and inclusive of all aspects of visualization use. It also promotes the idea of each individual having their own visualization skillset which can include different proficiencies for different visualization skills, and can better represent how different individuals may be more specialized in specific areas of visualization.

Future work can continue to build on our ideas by carefully constructing frameworks and models for the visualization skillset, investigating which skills are relevant and separable, which skill levels are meaningful and measurable, and how these skills may be related, grouped, or hierarchicalized. Existing understandings of these skills and how they relate are biased by the focus on communication contexts, leading to, for example, groupings that separate interpretation and construction. Future work that aims to understand the relationships between these skills should carefully consider whether these groupings make sense in all contexts. Skills in these models may include high-level visualization-relevant abilities such as interpretation or construction, as visualization literacy is currently understood, but may also be broken into finer-grained components such as reading individual points off of a chart, reading a trend from a chart, comparing existing knowledge to that presented in a chart, cognitively correcting for misleading chart designs, identifying whether a chart is trustworthy based on design and data source, identifying ways to improve the design of a chart, select a reasonable idiom for a certain dataset and task, or identifying statistical distributions in a chart.

These future frameworks should also consider other relevant skills, many of which use the analogy to literacy, such as numeracy, visual literacy, and data literacy. In particular, we should investigate the overlap between data literacy and the visualization skillset, and investigate whether the visualization skillset is a subset of data literacy or if some aspects of visualization, such as artistic uses of visualization, do not overlap. Constructing models that break visualization use down into multiple components would support work that investigates relationships with these other umbrella terms.

Future work should also be clearer about framing. In particular, it should describe the specific skills and skill levels which are relevant. This clarification will help to identify gaps so that other work can fill them and to reduce biases introduced by the issues to the textual literacy analogy. For example, assessments for the ability to read visualizations should consider differentiating between the skills of interpreting familiar charts and decoding unfamiliar charts. Similarly, assessments focused on the construction of charts can consider different levels of the skill, from selecting an effective idiom for a problem and dataset from a provided list to developing novel designs to support unique tasks. Future work can also assess existing work in detail, with respect to any new models or frameworks, to create a clear map of what aspects of this skillset have the most coverage and which are most in need of more study.

Finally, future work can continue to develop visualization skillset assessments, focusing on covering existing gaps. As funda-

mental skills have been the most well covered so far, more advanced skills should be prioritized. Assessing higher skill levels will likely be much more complex, less generalizable, and less easily measurable. This challenge aligns with textual literacy, where assessing career-level literacy is difficult due to specific, niche vocabulary, writing styles, and uses of text in different communities [29]. These assessments will likely need to become more targeted to specific visualization idioms, tasks, and user bases to remain helpful. For example, assessments for some professional data analysts may benefit from the inclusion of questions that target the user’s ability to identify statistical distributions in visualizations and make other connections to statistical models. One example of a targeted area of study underneath the visualization skillset umbrella is network visualization literacy, which involves how network data can be converted into visualization and whether people understand properties of the networks [39]. An even more targeted work is Firat et al’s treemap interpretation assessment [14], which can be considered a sub-skill of network visualization literacy as the treemap is a type of network visualization.

Visualization educators will be able to make use of these more nuanced models and assessments to improve how they teach and assess students. They will be able to understand which specific skills students need the most support for. They will also be able to assess students more accurately at higher skill levels or for specific skills relevant to the domain or use of visualization being taught. Overall, these improved models and tools will lead to a better understanding of visualization and the skills associated with it, as well as a more visualization-capable world.

5 CONCLUSION

In this paper, we presented the idea and terminology of the visualization skillset to support a more modern understanding of the ability to use visualizations than the term visualization literacy allows. We were motivated to develop this idea by two issues with visualization literacy’s analogy to textual literacy: the lack of an analogy for analysis contexts and the inherited false dichotomy of literate and illiterate. We argue that these issues have influenced and restricted visualization literacy research. We also discuss how future work can use and build on these ideas to contribute more complete models and more targeted assessments that fill existing gaps, leading to an improved understanding of visualization skills and better visualization education.

ACKNOWLEDGMENTS

This work was partially supported by the National Science Foundation (NSF) under Award Numbers 2142977 and 2330245. The authors wish to thank Francis Nguyen, Matt Oddo, Ryan Smith, and Steve Kasica of the UBC InfoVis group as well as Theresa Eingarner for their thoughtful feedback while developing these ideas and writing this paper.

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