# Conceptions of data literacy in the statistics education literature

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## Abstract

Data literacy is an increasingly important skill in our data-driven world, and librarians and other information professionals can play a key role in creating a data literate population due to data literacy's close association with information literacy. However, the definition of data literacy and the attention paid to certain competencies varies greatly between fields: what librarians and statisticians mean by "data literacy" is not the same thing. A scoping review of data literacy articles within the field of statistics education reveals the landscape of data literacy education in statistics, giving librarians and other information professionals a map for coordinating their data literacy work with disciplinary faculty. The areas of data discovery, evaluating and ensuring the quality of data and its sources, and reproducibility are closely examined. These areas are defined and valued inconsistently amongst information professionals and statisticians, but their close associations to traditional library services create an ideal opportunity for libraries and data archives to contribute to data literacy education.

## Keywords

Data literacy, statistics education, reproducibility, data discovery

## Introduction

Statistics educators often serve as the primary providers of data literacy education, but there is a disconnect between what statistics educators value in data literacy instruction and what librarians and other information professionals see as foundational data literacy competencies. By reviewing the data literacy literature from journals that publish articles in statistics education, we have found which areas of data literacy are less prioritized in statistics education. These gaps around developing students' ability to find, critically evaluate, document, and preserve data align closely with the values and duties of librarians, data archivists, and research data management specialists, providing libraries with an opportunity to make substantial contributions to data literacy education.

## Literature review

Data literacy is still an evolving field, and the exact definition of data literacy has not yet been settled. For example, Pinto et al. (2023) found in their systematic review of the literature that discussed both data literacy and information literacy that 45.59% of the 68 included articles provided their own unique definition of data literacy rather than citing a pre-existing definition.

Despite (or perhaps because of) this diversity of definitions, there have been several attempts to establish a consensus definition of data literacy. These efforts have typically involved comparing the competencies that are mentioned in competing definitions of data literacy in search of common themes or areas of overlap. For example, Bonikowska, Sanmartin and Frenette (2019) compared five different data literacy frameworks that were intended for use with broad, general populations of students or working adults. They found twenty-seven different competencies that were mentioned in just those five frameworks. Even worse, only five of the competencies appeared in all five frameworks: data discovery, data manipulation, evaluating and ensuring the quality of data and sources, basic data analysis, and data interpretation. Extending this line of work, Downes (2023) examined twenty different publications that provided lists of competencies that a person needed to achieve to be considered "data literate." The origins of these twenty publications varied. Several were produced by government agencies, such as the Australian Bureau of Statistics and Statistics Canada; others were written by academic researchers. In those twenty works, Downes identified forty different data literacy competencies that were mentioned at least once, and not a single one of those forty competencies appeared in all twenty of the works that he examined. He did, however, find that these competencies tended to cluster into five different data literacy models: the data stewardship model, the analysis and decision-making model, the information literacy model, the science and research data literacy model, and the social engagement model (Downes, 2023, p. 109).

Downes' (2023) information literacy model for data literacy is an obvious bridge to the library's domain, and librarians and other information professionals can find strong links from their skillset to the other models. Like information literacy, data literacy definitions are conceptualized as both a "specific skill set and a knowledge base, which empowers individuals to transform data into information and into actionable knowledge" (Koltay, 2017, p.17). While definitions of data literacy fluctuate in library and information science literature, the most cited data literacy competencies are "access, interpret, critically evaluate, manage, handle, and ethically use data" (Pinto Molina et al., 2023, p.15). In addition to data literacy's links to information literacy, librarians and data archivists are also well-situated to assist with data literacy services as they are highly connected to existing library workflows, such as information discovery, dissemination, publication, and subject-specific services (MacMillan, 2014). Libraries are also experienced in "fostering cross-departmental, cross-campus, etc. communication and collaboration," which is needed for effective research data management and data literacy education as data needs become ever more interdisciplinary (Koltay, 2017, p.8).

### Data discovery

Bonikowska, Sanmartin and Frenette (2019) found that two core information literacy skills as they relate to data—data discovery and evaluating and ensuring the quality of data and sources—were two of the five competencies that appeared in all five of the frameworks they investigated.

Data discovery is the process of finding relevant data to meet a research need (Gregory et al., 2018). Students competent in data discovery can access data from a range of sources rather than using data they collect themselves or that is directly given to them (Ridsdale et al., 2015). However, the term is used inconsistently. Librarians use the term in reference to the information-seeking aspect of finding existing data sources, while statistics and math educators often use the term "discovery" to refer to finding patterns, actionable insight or other areas of interest in the data at hand (Wilson et al., 2021; Curley & Peterson, 2022; Hassad, 2020; Roth & Temple, 2014). It is also used in the context of the constructivist approach of student-centered discovery within data education (Dangol & Dasgupta, 2023).

The ability to find relevant data is critical to the work of researchers. Much like a literature review, data discovery can give researchers an idea of what others in their field have found and highlight gaps in the information landscape. Finding data to reuse is more efficient than replicating the data collection process, which isn't feasible for many researchers. Data discovery is also essential for information evaluation, as researchers should be able to trace claims back to the original data, preform their own analysis to confirm claims, and locate and interrogate the accompanying documentation for biases.

Despite the importance of data discovery to the quantitative research process, previous scholarship has shown that many researchers struggle with this competency. According to Sun et al. (2024), researchers often turn to data support specialists for data discovery help for both exploratory searches for new data and for known-item searches. Their issues with discovering data lie in a "lack of data search skill, lack of data literacy, and lack of access to data" (Sun et al., 2024, p.8). Most researchers find datasets through their interpersonal connections or through the data's citation in text-based sources such as articles (Mathiak et al., 2023; Million et al., 2024). If that fails, they turn to open web searches (Sun et al., 2024). In contrast, data librarians and other data support specialists are adept at data discovery and find that data discovery services make up the bulk of their support interactions. Data support specialists are more likely to approach data discovery differently than literature discovery and are more adept at using a variety of sources like search engines, domain repositories, and governmental sources. However, few librarians have the specialized training needed to be confident in their data discovery skills as there is a clear difference in the way data is cataloged, stored, searched for, accessed, and used compared to traditional library materials (Huck, 2020; Million et al., 2024).

### Evaluation and ensuring quality of data

Evaluating and ensuring the quality of data is a critical skill for a data literate population and is another common competency across data literacy models and definitions (Bonikowska et al., 2019). This skill involves critically considering the trustworthiness of data and its sources, identifying errors in data, evaluating if captured data represents the original information correctly, and determining the quality of data and assessments. Data literate people know that when evaluating data, they are evaluating "1) trustworthiness of the measurement 2) trustworthiness of the data processing and 3) trustworthiness of the data integration and visualization" (Koedel et al., 2022, p.1). Like information evaluation, there are several different data quality models that serve as benchmarks for characteristics of high-quality data. The ISO/IEC 25012 Data Quality Model, for example, lists and defines 15 characteristics such as accuracy, credibility, currentness, compliance, and traceability (ISO/IEC 25012, 2008). Some data repositories, such as Kaggle.com, created data quality assessment scores, but their basis for score calculations are often unclear or evaluate aspects of the dataset that have little bearing on the actual quality of the data. For example, having a cover photo for the dataset increases its quality rating on Kaggle.com (Chicco et al., 2025). Furthermore, these data quality models are often dependent on which field of research they were created in, which means that there may be elements that are irrelevant when applied from, for example, soil composition data to pharmacology data. Despite these differences, most models agree that high-quality data represents the real-world accurately, and has attributes of "accuracy, correctness, currency, completeness and relevance" (Bertino, 2015, p.19).

Evaluating and ensuring quality of data looks different depending on the role of user. Both data creators and data consumers need to actively evaluate and ensure the quality of the data at hand. Data creators have several crucial responsibilities: they must ensure the accuracy of their measurements, critically examine their collection process for potential biases, properly address missing data and outliers, reflexively evaluate their own potential biases, and provide comprehensive, "thick description" or context for their data (Korstjens & Moser, 2018, p. 122). These steps aid in the reproducibility and appropriate reuse of their data. When evaluating data, data consumers must consider the intrinsic data quality and the contextual data quality of the externally produced data (Mahanti, 2019). Intrinsic data quality considers the elements of the data itself, as discussed above, such as completeness, accuracy and consistency. Contextual data quality refers to the users' own context, such as their research question and purpose for using the data.

Much of the library literature discusses the quality of data in terms of research data management and working with data creators to better preserve, describe, store, and share their data (Giarlo, 2013). Evaluating the quality of data and its sources for externally produced data is widely discussed in the library literature, but typically in vague terms. Often, library literature will discuss evaluating data-based claims or conclusions in media and other sources using information literacy frameworks, such as Brungard and Smith (2021). While these skills can certainly be applied to data and data sources, they do not necessarily address how to identify the previously discussed data quality models' attributes of high-quality data. Other library literature stressed the importance of evaluation of data sources but does not directly state what qualities need to be evaluated (Carlson et al., 2015). Others state some characteristics of high-quality data as defined by the data quality models, such as Arellano Douglas et al. (2021), when they provide an evaluation learning objective where "students will critically examine data for accuracy, reliability, bias and context" (p.43). The vagueness about what characterizes high-quality data, and which attributes should be the focus when evaluating data extends outside of the library. Sapp Nelson (2014) highlighted this in their study in which a faculty member "focused on using critical thinking to evaluate the contents of an externally produced data set for quality", but "did not describe the actual metrics by which an individual evaluates data quality" (p.232). This provides an opportunity for librarians to collaborate with faculty to better understand and teach data evaluation skills.

## Methodology

To create our corpus, we searched 11 journals that were identified by the Consortium for the Advancement of Undergraduate Statistics Education (CAUSE) as publishing research related to statistics education: *Technology Innovations in Statistics Education (TISE), Journal for Research in Mathematics Education (JRME), Educational Studies in Mathematics (ESM), Mathematical Thinking and Learning (MTL), International Journal of Mathematical Education in Science and Technology, International Statistical Review (ISR), The American Statistician (TAS), Mathematics Teacher (MT), Teaching Statistics, Journal of Statistics and Data Science Education, Journal of Statistics Education,* and *Statistics Education Research Journal* (CAUSE, n.d.). We decided to limit the search to these journals so as to address the landscape of data literacy specifically in statistics education, and not other disciplines, which may cover different competencies of data literacy. Furthermore, articles about data literacy education are not consistently described, making searching a broader corpus difficult and inaccurate. By targeting this curated set of journals that publish articles in statistics education, we also intentionally focus on educational settings that range from primary schools to graduate students. While limiting a scoping review to specific individual journals is not a common practice, it has been done in several fields (Maggio et al., 2021; Logan et al., 2024; Medeiros et al., 2024).

We further limited our search to articles published within the last 12 years to evaluate only current literature on the topic. Due to the large volume of articles that mention data literacy in passing, we searched for the term in the title, abstract or keywords of the articles. Additionally, we experimented with search terms that would include articles that addressed the concept of data literacy education. Over 40 different search terms were tested in 12 different search queries in the Scopus database, as it indexed all of the identified journals. The results of each search were reviewed, comparing the total number of results and the relevancy of the articles' titles and abstracts to the research goal and to the other search queries' results. This review was done by exporting the results to a spreadsheet, manually scanning the results' titles and abstracts for relevance to our research question, marking the results, and comparing them to the other searches' results. The final search string, which is reproduced below was chosen for its adequately scoped results that were highly relevant to the research goal.

> ISSN ( 1570-1824 OR 2693-9169 OR 10691898 OR 1933-4214 OR 0021-8251 OR 1573-0816 OR 1532-7833 OR 1464-5211 OR 0306-7734 OR 1537-2731 OR 1467-9639 ) AND PUBYEAR > 2012 AND PUBYEAR < 2024 AND TITLE-ABS-KEY ( student* OR literacy OR education OR class OR classroom OR curriculum ) AND ( TITLE ( "data literacy" OR "statistical literacy" OR data ) OR KEY ( "data literacy" OR "statistical literacy" OR data )

Another manual review of the articles was undertaken to remove irrelevant results. Articles that focused on purely pedagogical practices, such as articles detailing the effectiveness of flipped classroom course designs, or articles that focused primarily on discussing mathematical concepts, were removed from the corpus as they did not discuss the data literacy competencies that educators wanted students to learn. Articles that used simulated data rather than real-world data were also removed from the corpus. Simulated data does not provide students with the opportunity to work with several key data literacy competencies, such as evaluating the quality of data and its sources and data collection, and it removes the connection of data from the important real-world contexts. A small number of articles were removed as they either were not research-based articles (e.g., editorials) or their connection to data literacy education was minimal. This left us with a corpus of 260 articles.

| Criteria | Inclusion | Exclusion |
| --- | --- | --- |
| Topic | Data literacy education learning outcomes | pedagogical strategy focus; mathematical concepts |

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| | | without a data literacy education component; |
| Data Context | Use of real-world data | Use of simulated or synthetic data |
| Publication Date | 2012-2024 | Articles published outside of the data range |

The corpus of articles was loaded into the NVivo qualitative data analysis software for analysis. Each of the articles was coded to indicate whether the full-text contained any mention of each of the 27 data literacy competencies mentioned in Bonikowska, Sanmartin and Frenette (2019). (See Appendix A for a list of those 27 competencies.) If an article contained any indication, even in passing, that the author or authors of the article believed that achieving a given competency was a worthwhile outcome of statistics education, that article was coded as mentioning that competency.

## Results and discussion

On our first pass at coding the articles, we identified several codes that could be applied to a near-majority or a majority of the articles, including basic data analysis, data visualization, data interpretation, and data tools. This is expected, as these competencies are traditionally the focus of data or statistics education. However, interdisciplinary competences were also highly represented. Critical thinking was a common theme, which aligns with a shift in statistics education that encourages connecting students to real-world data and its implications (Ferris & Cheng, 2018; Koga, 2022; Ben-Zvi & Garfield, 2004). Communication skills were also highly valued, with slightly less than half of the articles mentioning the importance of students' abilities to present their findings verbally.

Given the ubiquity of these codes and, in many cases, their lack of a clear connection to the aspects of data literacy that are most relevant to the work of libraries and data archives, we chose not to pursue them further, and instead to focus on our analyses on other data literacy competencies.

### Data discovery

Data discovery was only mentioned in 30 of the 260 articles (11.53%). Of those articles, 12 (4.62% of the overall corpus) mentioned data discovery in passing (i.e., mentioning that students were expected to find an outside data source for an assignment). Another 14 articles (5.38%) mentioned data discovery outlined specified data sets or data sources as recommendations for educators to use with their classes. However, 9 of the 35 mentioned sources are no longer widely available for use or are significantly out of date, and another 10 belong to US government agencies that are currently facing mass information suppression. This highlights the issue of providing sources without accompanying skills as sources are prone to disruption, while skills can be more widely applied to various statistical inquiries and can better stand the test of time.

Only 4 articles (1.53%) in the corpus discussed relevant skills that students would need to facilitate data discovery outside of classroom-provided materials. One of these articles (Fergusson & Wild, 2021) discussed APIs. While articles about APIs were typically listed as "data collection" or "data tools" in the coding, this article prompted students to find their own data sources using APIs and highlighted the importance of combining data from different sources. Another article (Caballer-Tarazona & Coll-Serrano, 2020) featured a learning goal that students "become familiar with an official data base and realize that even if data are available, key skills are required to manage the data and extract and understand the available information" (p.309), which is a critical aspect of data discovery.

One article (Çetinkaya-Rundel et al., 2022) provided guidance for student's data discovery. They stated, "An approach where students are given only guidance, but not a list to pick a dataset from, gives them full control over their project" (p.6), highlighting the importance of data discovery for undertaking the data inquiry process. Their first guideline prompts students to think about their questions and what sort of variables and units would be needed in their desired dataset. They go further to state that their question may not have a readily available dataset, so they may need to revisit the question they are asking until they find "a happy medium" (Çetinkaya-Rundel et al., 2022, p.6). The authors also recommend the services of librarians as they "are helpful in locating data to answer specific questions as well as helping students restate their questions to better match the data available" (Çetinkaya-Rundel et al., 2022, p.6).

This absence of focus on data discovery skills is not surprising when considered in the context of existing literature on data discovery. As discussed above, researchers often turn to data support specialists for data discovery assistance (Sun et al. 2024). Researchers rely on interpersonal connections or literature searches for their data needs, and this is replicated in the classroom. Students and researchers would benefit greatly from librarians' expertise in strategically searching for data. Librarians are well-situated, if not always well-trained, to help with data discovery efforts. Data discovery is information-seeking, and as such it requires parallel skills to traditional information discovery, such as source evaluation, search queries, and knowledge of appropriate databases.

### Evaluation and ensuring quality of data

In the corpus, 51 articles (19.62%) discussed elements of evaluating and ensuring quality of data. It is important to note that we coded articles that discussed evaluating conclusions, analyses, or claims to the code "evaluating decisions and conclusions based on data," leaving only articles that discussed the quality of data and datasets. Additionally, articles that discussed quality of data in terms of research data management competencies were coded to other competency codes such as data duration and reuse. Fourteen of these articles (5.38%) mentioned this competency in passing, vaguely referring to the importance of evaluating data but without any specific discussion of what that entails from either the position of a data creator or a data collector. Fifteen articles (5.76%) discussed ensuring the quality of one's own data, typically in reference to data collection methods (Frölich & Schellhammer, 2022; Zhu et al., 2013), measurement (Casleton et al., 2014), variability (Roth & Temple, 2014), sampling, and evaluating models to see if they accurately represented real-world phenomenon (Fleischer et al., 2022). Very few of the articles discussed data quality in terms of the data quality models. Bilgin et al. (2022) stands out, as they discuss the use of a quality manual and documenting the project in terms of Cross Industry Standard Process for Data Mining (CRISP-DM). Zhu et al. (2013) did not directly relate back to a specific data quality model, but listed in-depth, systematic quality control measures that would match with previously discussed data quality attributes such as critical examination of their collection process for potential biases, properly addressing missing data and outliers, precision in measurements, and detail reporting of context.

The remaining 26 articles (10%) discussed evaluating the quality of externally produced data. Most of these articles focused on asking critical questions of the data such as who created the data, how they gathered it, and its original purpose, such as Delport (2023) with their use of "worry questions," and Lee et al. (2022) with their discussion of the issue of bias, both in what is represented in the data and what is not represented in the data. This focus on bias relates to a broader competency of critical thinking, which was far better represented in the data literacy literature, with 138 (53.01%) articles covering the topic. While evaluating and ensuring quality of data and sources certainly requires a level of critical thinking, it is more specific in the goals of the critical questioning than critical thinking alone does. It is not enough to ask the questions like, "Who made this?" and "What sort of biases could be present?." To truly evaluate the quality of data and its sources, one must be able to find the answers to those questions and, potentially, know how to compensate for the weaknesses in data or its sources. However, directions for asking the questions are rarely followed with instructions on how to find the answers to such questions.

Few of the articles coded as "evaluating and ensuring quality of data and sources," discussed how students could find information to answer the questions they were asking of the data source outside of an accompanying data dictionary. While a data dictionary would be important for this task, much of the available data does not come with a data dictionary or codebook. Lee et al (2022) suggests that it may "be necessary to reach out external stakeholders or experts to find additional information about the data context" (p.14) to answer questions about the quality of data. Other articles suggested comparing findings with other sources, which is an essential skill in both data literacy and information literacy. However, there is a gap in data discovery skills, as previously discussed. Without strong data discovery skills, it would be difficult to find an alternative data source that matched the important features (i.e., research focus, method, measurements, categories, etc.) sufficiently to make a meaningful comparison. Besides these suggestions, none of the articles prompted students to do their own research on the source of the data, instead relying on educators or the data providers themselves to provide all the necessary context for the data.

Overall, the articles in the corpus stressed the importance of ensuring and evaluating the quality of found data but did not discuss how to teach practical skills for doing so. Çetinkaya-Rundel et al. (2022) provide the most practical directions for evaluating found datasets in their guidelines for student-selected datasets. They set basic standards in terms of number of variables and observations that need to be present in a dataset to account for confounding variables. They also require that students use data that includes a "comprehensive" data dictionary, stating, "Without these, it is impossible for students to evaluate the reliability, validity, and ethical considerations of the data for their projects" (Çetinkaya-Rundel et al., 2022, p. 6). The article warns students to be selective about using data from aggregators, citing concerns over varying states of documentation for and the use of sample data analyses in the datasets. Still, this article, like the others in the corpus, did not discuss the characteristics of high-quality found data that are mentioned in data quality standards, such as consistent, unambiguous, and current (Mahanti, 2019; ISO/IEC, 2008). Some mention these characteristics in passing (e.g., Jones, 2020), but there is not a clear discussion of how students can spot the presence or lack thereof of these characteristics. While librarians can apply information evaluation skills to assist in this area, some consensus would be needed on what metrics and attributes qualify data as high-quality.

### Reproducibility: A disconnect between librarians and statisticians

Reproducibility and reproducible research workflows were common themes in these articles. In the included articles, reproducibility typically means computational reproducibility: "A reproducible analysis is one that can be rerun (potentially years later, or by a different person) with the same data to produce exactly the same result" (McNamara, 2019, p. 381). While computational reproducibility is important, it is not the only form of reproducibility. Some other fields strongly emphasize other forms of reproducibility, even to the point of defining "reproducibility" differently. For example, Plesser (2018) compiled definitions of reproducibility and the related concepts of "repeatability" and "replicability" from a number of scientific fields, including geophysics, chemistry and computer science. As Plesser noted, the idea of reproducibility inherent in "computational reproducibility" "is at odds with the terminology long established in experimental sciences" (Plesser 2018, 1), which uses "repeatability" to describe the condition where the same procedure run on the same equipment under the same conditions produces the same results. In those fields, "reproducibility" means the ability of a different research group, using different equipment, to produce the same results. To make the matter even more confusing, some fields use an additional term, "replicability," which, depending on the field, can mean something closer to "computational reproducibility" or something closer to the experimental sciences' definition of "reproducibility" (Plesser 2018).

Existing models for data literacy are more closely aligned with the experimental sciences' definition of "reproducibility" than with the concept of computational reproducibility. No competencies that directly map to the concept of computational reproducibility appear in either of the compilations of data literacy competencies that were discussed in the literature review of this article (Downes 2023 and Bonikowska et al. 2019). Instead, the data literacy models that were compiled in these two reviews emphasize competencies such as data curation, data preservation, and data sharing, which are necessary to allow for research results to be reproduced by other research groups. Yet very few of the articles included in this analysis mentioned the data literacy competencies such as these that would allow researchers to make sure that other researchers outside of their own circles, or that the researchers themselves in the long-range future, could access and use the data necessary to reproduce their research.

For example, data preservation (ensuring that the data is preserved in its original state for the duration of the student's or researcher's period of analysis) and data duration and reuse (ensuring that data is preserved in its original state indefinitely, and in such a way that it can be made available to and reused by other researchers) are rarely discussed explicitly using those terms, although both aspects are inherent in the experimental sciences' definition of reproducible research.

For the purposes of this project, we assumed that, unless the context clearly indicated otherwise, any mention of "reproducibility" in these articles included data preservation as one of the implicit goals. This assumption is due to the typical structure of the projects discussed in the articles, where students were expected to turn in their original data files, along with any code that was used to manipulate or analyze the data, allowing the instructor to reproduce the students' entire data processing and analysis procedure. With this generous definition of data preservation, 66 articles (25.38%) were coded as mentioning data preservation. However, these articles rarely explicitly call out "not altering the original data file" as one of the benefits of a reproducible analysis. Also, some of the articles discuss reproducible research *workflows*—being able to run the exact same analysis steps on a *different* dataset, rather than on the same dataset. Where it was clear that reproducible workflows rather than reproducible analyses were being discussed, the article was not coded as "data preservation." Given all of these caveats, it is difficult to say precisely how frequently students are explicitly being taught about the importance of preserving a copy of their original data file.

Conversely, we did not assume that "reproducibility" referred to data duration and reuse and data sharing unless those competencies were explicitly mentioned. This assumption contributed to a much lower number of articles being coded to the "data duration and reuse" and "data sharing" competencies: 16 (6.15%) and 10 (3.85%), respectively. The concept of metadata creation also appeared infrequently, in 11 articles (4.23%), although typically in the guise of "codebooks" and "data dictionaries": forms of metadata that are very useful for accurately interpreting a given dataset, but that are less helpful for dataset discovery.

Data citation was mentioned in only three articles (1.15%), and always in passing. A lack of data citation skills is likely to hamper reproducibility, given that many datasets that may be used in research have contractual or ethical restrictions that prevent them from being freely redistributed by the researchers who use them. If students do not learn how to cite data properly, people in the future who wish to replicate their analysis may be unable to identify and access the specific dataset that was used. Similarly, data sharing was mentioned in only 10 articles (3.85%), again usually without any sort of detail about issues to be considered or specific tasks to be completed in order to share data ethically and effectively.

A good example of a typical discussion of data sharing in this corpus can be found in Donoghue, Voytek, and Ellis's article "Teaching Creative and Practical Data Science at Scale," (2021), which focuses on the skills that students need to learn to be effective data science professionals (see pp. S33-S34).

The authors list many specific practices and skills that students must master to be able to carry out reproducible research, but most of these skills are related to the code that implements the analysis rather than the data that is being analyzed. The code must be "well-organized, documented, and tested;" it must be "understandable by other analysts." The data, however, only needs to be "stor[ed] . . . in a consistent manner." All of the other skills and practices necessary for ethical and effective data sharing go unmentioned.

## Conclusion

Although this study, which only examined published journal articles, demonstrated which data literacy competencies are well-covered in the statistics education literature and which are not, it does not and cannot explain why the missing competencies are not covered. Future research in this area should draw on a wider range of sources, in particular conversations with statistics educators about their views of the missing data literacy competencies. Do statistics educators not think these competencies are important? Do they not feel equipped to teach them themselves? Do they believe that they are being covered in classes outside of statistics? Without answers to questions such as these, it is not clear how librarians and other information professionals can best position ourselves to help. Data librarians and research data management specialists are well-equipped to teach the data literacy skills that are apparently not being covered in statistics education, as these skills are of deep interest to these professions, but becoming empowered to teach these skills to students in statistics classes will require collaboration with statistics educators and a richer understanding of statistics educators' perspectives on data literacy.

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## Appendix A: Data Literacy Definitions

The codes used for this review were collected from Bonikowska et al., 2019, which compared competencies of data literacy found in Data to the People (2018) [1] ; Grillenberger & Romeike (2018) [2] ; Ridsdale et al. (2015)[3]; Sternkopf & Mueller (2018)[4]; and Wolff et al. (2016)[5]. Below are the definitions of each competency that we synthesized from the five articles.

| Competencies | Definitions |
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| Basic data analysis (select appropriate tool/algorithms/analysis methods for data, knowledge and use of basic summary/descriptive statistics) | Basic data analysis involves developing and executing plans to examine data using appropriate tools, algorithms and analysis methods including descriptive statistics, hypothesis testing, linear regression, etc. [1,2,3,4,5] |
| Critical thinking (aware of high-level issues associated with data, thinks critically when working with data) | Critical thinking involves being aware of high-level issues and challenges associated with data while applying thoughtful consideration when working with it. [2,3] |
| Data culture (psychological barriers, attitudes, etc towards data) | Data culture refers to the recognition of data's importance and the fostering of an environment that promotes critical use of data for learning, research, and decision-making. It involves overcoming psychological barriers related to data, understanding its potential as an enabler for progress, and securing support from management for data initiatives and resources. [3,4] |
| Data collection (gathering data, structure gathered data, critically evaluate the collection process) | Data collection encompasses the process of gathering information in various formats and complexities to support specific needs. It involves selecting appropriate methods, implementing algorithms, and considering ethical issues and privacy impacts. [1,2,3,5] |
| Data conversion (from format to format) | Data conversion is the ability to transform data from one format or file type to another, requiring knowledge of different data types and conversion methods. [1,3,4,5] |
| Data ethics (security, privacy issues) | Data ethics involves understanding and addressing the moral implications of collecting, analyzing, and using data. It requires considering privacy concerns, potential biases, and the societal impact of data-driven decisions. Advanced practitioners can develop ethical frameworks, guide others in ethical data practices, and advocate for responsible data use within organizations. [2,3,4,5] |

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| Data discovery (ability to find and access data, connect data from different sources, identify useful data) | Data discovery is the ability to find, access, and identify relevant data from various sources. It progresses from using basic search engines to understanding and selecting from a wide range of data sources, including specialized data portals. Advanced skills include assisting others in locating data and formulating assessment criteria for selecting the most relevant data sources for specific informational needs. [1,2,3,4,5] |
| Data driven decision making (Prioritizes information garnered from data, converts data into actionable information Weighs the merit and impacts of possible solutions/decisions, Implements decisions/solutions) | Data-driven decision making (DDDM) is the process of using data to inform and guide strategic choices. It involves analyzing relevant data, converting it into actionable insights, and weighing potential outcomes to make informed decisions. Those skilled in DDDM can also communicate and defend their data-based decisions. [1,3,5] |
| Data duration and re-use (structure data in suitable way for storage and other's re-use, curation requirements) | Data duration and re-use refers to the process of structuring and storing data in a way that facilitates long-term preservation and future utilization by others. This competency involves assessing curation requirements, implementing appropriate storage methods, and ensuring data accessibility while considering ethical and security concerns. [1,2,3] |
| Data interpretation (understanding data, read and understand charts & tables, find key points and relationships in data) | Data interpretation is the ability to understand and extract meaning from data outputs such as analyses and visualizations. It involves identifying key points of interest, recognizing relationships within data, and critically assessing the implications of data outputs. [1,2,3,4,5] |
| Data management and organization (store and organize data appropriately for the analysis) | Data management covers the practices of organizing and storing data for the length of the analysis process. [1,2,3] |
| Data manipulation (data cleaning, knowledge that most data is not clean, combine data, decide when it is appropriate to combine | Data manipulation involves transforming, cleaning, and restructuring data to make it suitable for analysis. At a basic level, data users know that most data are not clean and that cleaning the data is necessary for analysis. Skills range from basic sorting and filtering to advanced techniques like appropriately removing outliers and anomalies and deciding when it is appropriate to combine data. [1,2,3,4,5] |

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| data, remove outliers and anomalies) | |
| Data preservation (decide which data to keep or delete, identify appropriate ways to store data) | Data preservation encompasses determining which data to retain, who should have access, how to ensure the integrity of the data, and how to ethically handle data deletion. Effective data preservation ensures data validity, addresses ethical considerations, and maintains data accessibility over time. [2,3] |
| Data sharing (decide whom to share data with from a legal or ethical perspective, prepare data for sharing) | Data sharing involves the practice of making data available to others, both within and outside an organization. It requires understanding of data formats, sharing platforms, and relevant legal and ethical considerations. [2,3] |
| Data tools (knowledge of and ability to use tools to collect, store, clean, organize, or analyze data, the ability to choose appropriate tool for the task) | Data Tools are software applications and techniques used for gathering, structuring, and analyzing data. They encompass a range of functionalities, from selecting suitable sensors for data collection and implementing algorithms to download data from web APIs, to applying various analysis techniques and visualization methods. Those literate in Data Tools have the ability to choose the appropriate tool for the task at hand. [2,3,5] |
| Data visualization (create meaningful graphs and charts, choose appropriate visualizations for the data or analysis) | Data visualization is the skill of creating meaningful graphical representation of data to facilitate understanding and insight generation. Those literate in Data Visualization not only make charts and graphs but also know the appropriate type of visualization for the data at hand. [1,2,3,4] |
| Data citation (Knowledge of widely accepted data citation methods Creates correct citations for secondary data sets) | Data citation is the knowledge and application of widely-accepted methods for crediting secondary data sets. It involves creating correct citations for data sources, ensuring proper attribution and enabling others to locate and verify the data used in analyses or research. [3] |
| Develop hypotheses (ask questions that can be tested, predict the outcomes of data analysis) | The ability to develop hypotheses includes being able to ask questions that can be tested and make informed predictions on the outcome of the data analysis. [5] |
| Evaluating and ensuring quality of data and sources (Critically consider the | Evaluating and ensuring quality of data and its sources involves critically assessing the trustworthiness, accuracy, and reliability of data and its origins. This process ranges from identifying errors or problems in datasets to critically evaluating data collection methods, sources, and |

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| trustworthiness of data, identify errors in data, evaluate if captured data represents original information correctly, quality assessment and data checking) | potential biases. It also encompasses the ability to verify data quality through multiple layers of checking and connect data from different sources, ultimately ensuring that the data used is representative and suitable for analysis and decision-making purposes. [1,2,3,4,5] |
| Evaluating decisions/conclusions based on data (collect follow-up data, compare with other findings) | Evaluating decisions/conclusions based on data involves assessing the effectiveness of actions or solutions by analyzing follow-up data and comparing results with other findings. This process includes collecting relevant data from various sources, conducting thorough analysis, and using the insights gained to either validate original conclusions or implement new decisions. The ultimate goal is to ensure that decisions are continually refined and improved based on empirical evidence, fostering a culture of data-driven decision-making and continuous improvement within organizations. [1,3] |
| Identifying problems using data (knowledge of which questions can be answered by the data) | Data literate people should be able to identify and describe problems in practical situations using a range of data sources. Questions should be formulated precisely and target-orientated to find meaningful answers. [1,3,4,5] |
| Metadata creation and use (apply metadata to datasets such as descriptors) | Metadata creation and use refers to understanding of what metadata associated with data sources are, why such descriptors are important, and the ability to create and assign appropriate metadata descriptors to original data sources. [1,3] |
| Presenting data verbally (data storytelling, describing key findings, communicate with others about findings) | Presenting data verbally involves clearly and coherently describing key insights, datasets, and visualizations in a way that aligns with the audience's needs and familiarity with the subject. This skill progresses from explaining simple data points to effectively using narratives, visualizations, and storytelling to communicate complex data in broader contexts. [1,3,4] |
| Undertake data inquiry process | Undertaking a data inquiry process involves a systematic approach to exploring and analyzing data to answer specific questions or solve problems. It is often done through the PPDAC model: Problem, Plan, Data, Analysis and Conclusion (Wolff et al., 2016).[5] |
| Work with large data sets | Working with large data sets refers to the ability to effectively handle, process, and analyze substantial volumes of data. This can include datasets that are voluptuous and complex like Big Data, datasets that |

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| | require multiple tools to handle effectively, or that combine diverse data types. [5] |
| Knowledge and understanding of data, its uses and applications | Data literacy involves understanding the nature of data, its various forms, and how it is produced. A data-literate individual should be aware of data's role and influence in society across diverse settings, as well as the ethical considerations associated with its use. |

## Appendix B: Article Corpus

Abel, T., & Poling, L. (2015). Hold my calls: An activity for introducing the statistical process. *Teaching Statistics*, *37*(3), 96–103. https://doi.org/10.1111/test.12082

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## Appendix C: Removed Articles

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## Endnotes

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