Mapping Public Open Access K–12 State Education Indicator Data Across 7 States and Washington, D.C. Using the FAIR Data Principles

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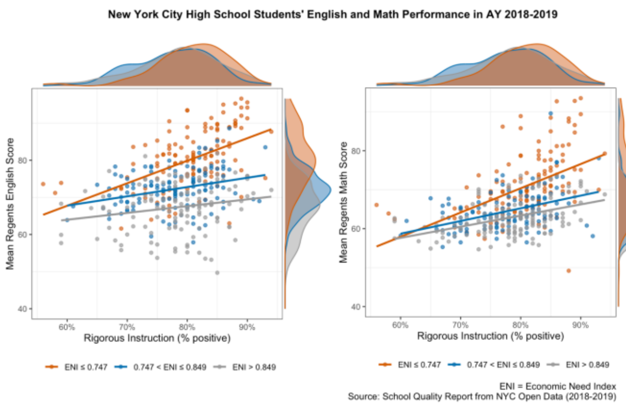
Teachers College Columbia University

Mapping Public Open Access K–12 State Education Indicator Data Across 7 States and Washington, D.C. Using the FAIR Data Principles



1. Data Science in Education Administration, Policy, and Practice
   - Bowers, A.J. (2025) Data Science in Education Administration, Policy, and Practice. In *AERA Handbook of Education Policy Research*, 2nd Edition. Cohen-Vogel, L., Scott, J., Youngs, P. (Eds.). American Educational Research Association; Chapter 29, p.585-612. https://doi.org/10.7916/amq5-ps80

2. Mapping 16 Education Indicators to the Universe of Public Open Data in New York City and 7 States and Washington D.C. using the F.A.I.R. Data Principles of Findable, Accessible, Interoperable and Reusable.
   - Bowers, A.J., Choi, Y., Shi, H., Sun, F., Sun, H., Williams, J., Weeks, S. (2022) Mapping 16 Equity Indicators to the New York City Schools Public Datasets: Access, Opportunity, and Outcomes. Teachers College, Columbia University. New York, NY.
     - Full Report Open Access CC:BY:NC: https://doi.org/10.7916/a143-aq05
     - Open access R Markdown code for all figures: https://doi.org/10.7916/q2zr-qd07

   - Bowers, A. J., & Choi, Y. (2023). Building School Data Equity, Infrastructure, and Capacity Through FAIR Data Standards: Findable, Accessible, Interoperable, and Reusable. *Educational Researcher*, https://doi.org/0013189X231181103

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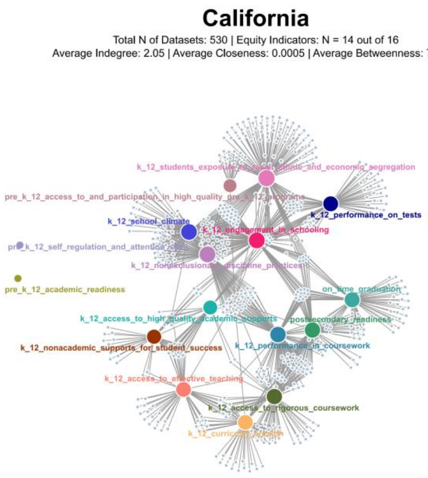
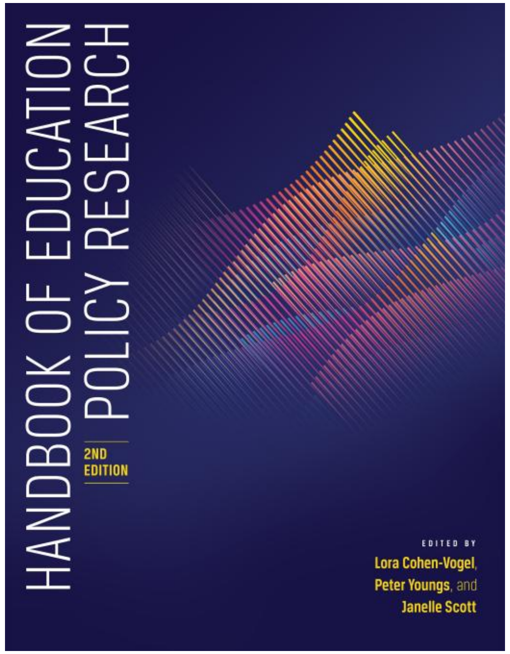
     1. California
     2. Kentucky
     3. Maryland
     4. North Carolina
     5. Oregon
     6. Ohio
     7. Texas
     8. Washington DC



Data Science in Education Administration, Policy, and Practice



Abstract:
Education data science has recently come to the fore as education systems globally produce increasing amounts of data. Yet, calls for applying machine learning, pattern analysis, and data visualizations to support decision making in organizations are nothing new, as these calls for what has come to be known as data science have been consistent for over 50 years. The purpose of this chapter is to overview the main components of education data science, and provide examples of how it can help inform education research, policy, and practice. Data science includes communicating with data, data analysis, and managing data, combined with domain knowledge, informing management and policy decisions through communicating and visualizing patterns, predictions, and the outcomes of decisions. This includes machine learning and open and shared data and code, ethics and attention to issues of bias, equity, and community, as well as a focus on prediction accuracy versus model fitting.

The full paper is divided into ten sections:

1. A definition of data science
2. 50 years of data analytics and decision making: A brief history
3. Education data science and the 21st century
4. Testing Management Ideas using Data Science and Experimentation
5. A Roadmap for Training in Education Data Science
6. Accuracy of Prediction versus Modeling Fitting
7. Machine learning only learns from data, data from a flawed and inequitable system
8. The Common Task Framework (CTF): Building Capacity in Data Science
9. Data Science as a Third Methodology in Education Research
10. Conclusion and a Look to the Future

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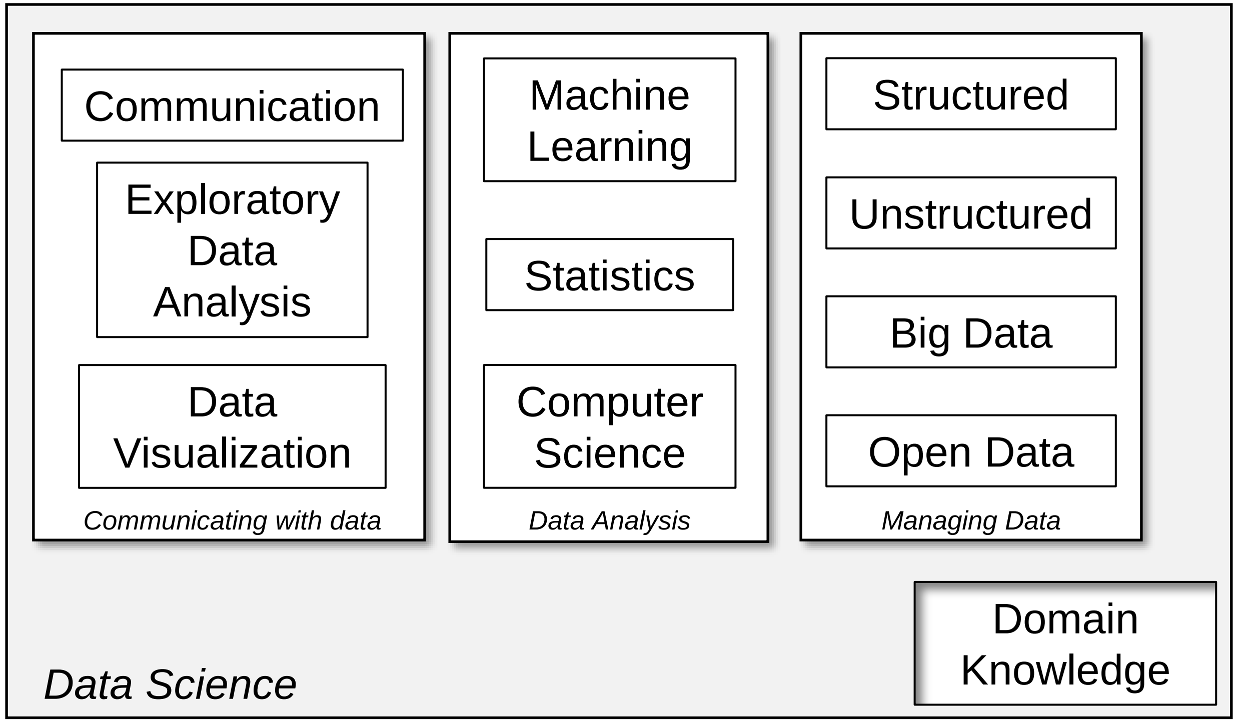

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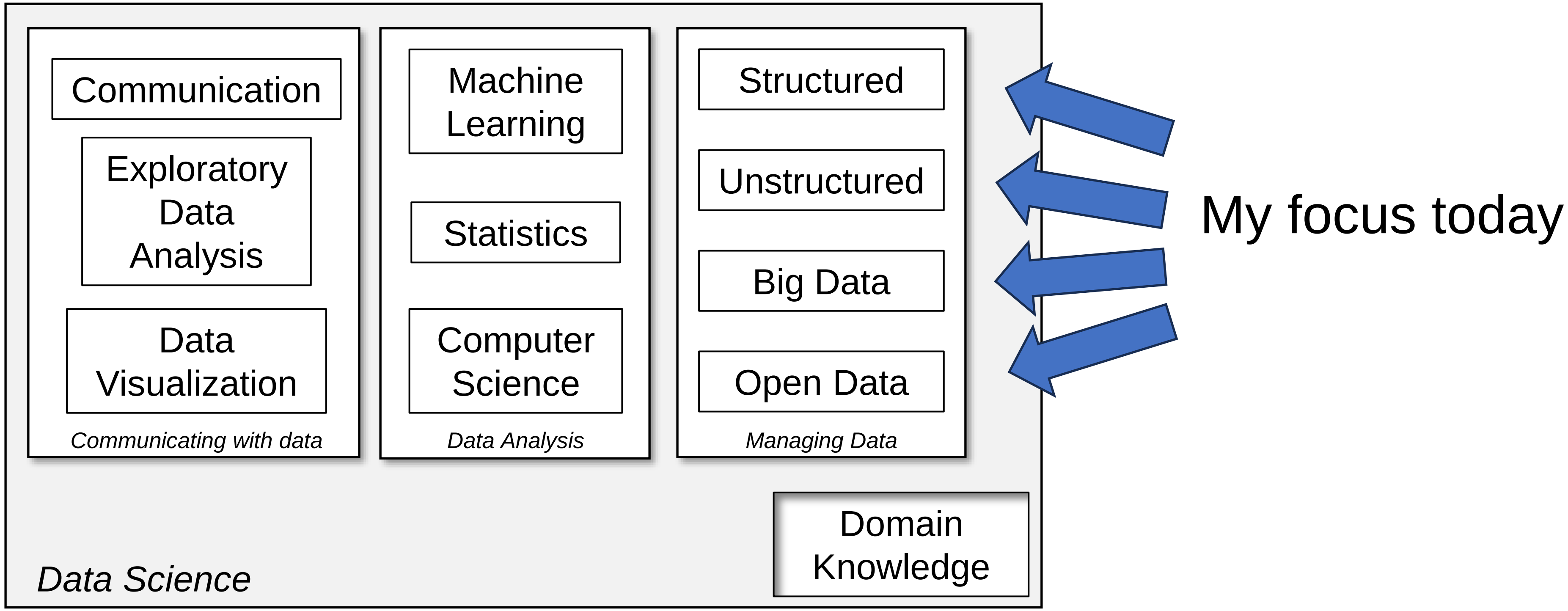

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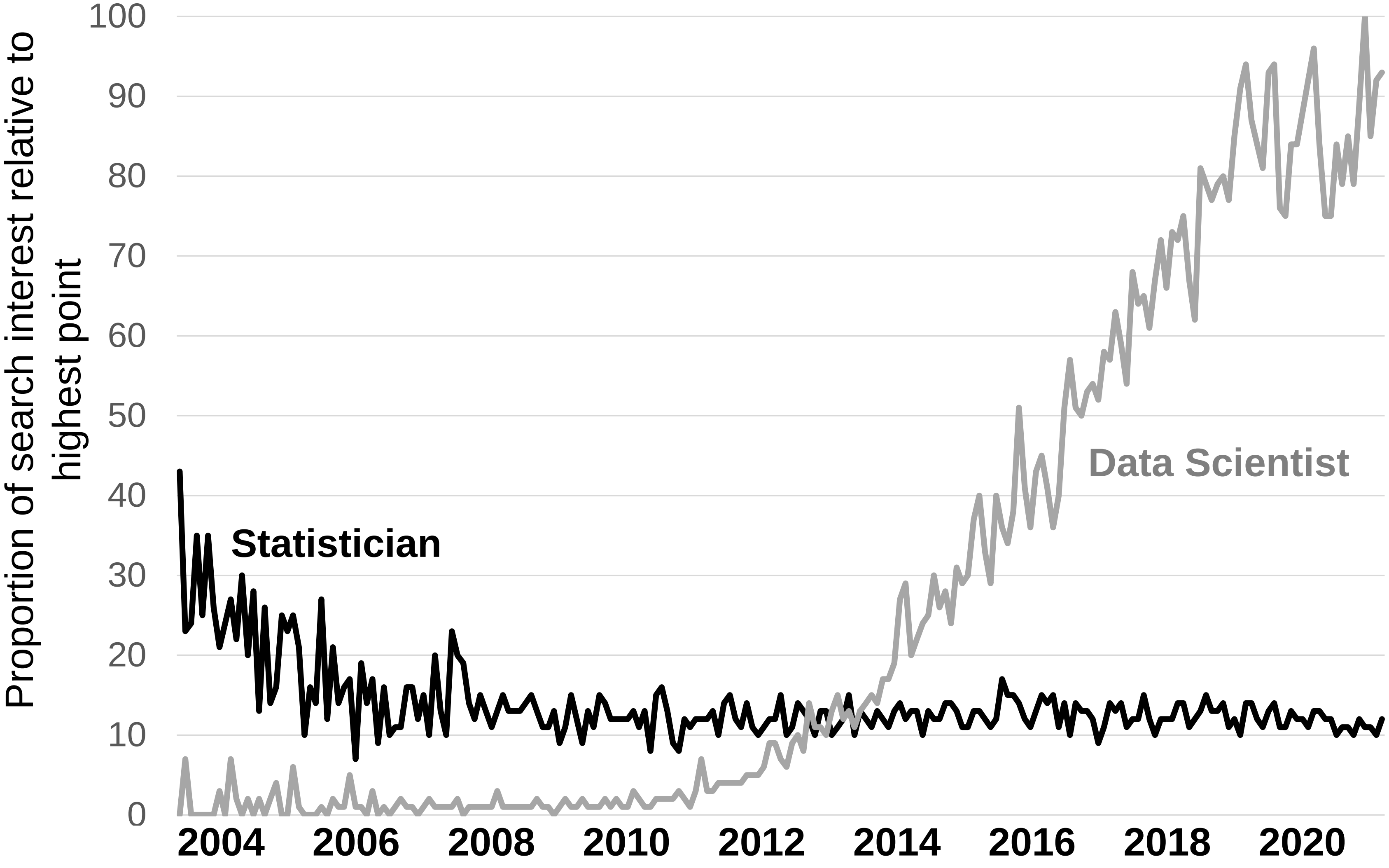

Figure 2: Data Scientist surpasses Statistician in 2013 on Google Trends. The x-axis is year from 2004 to 2021, the y-axis represents global Google search interest relative to the highest point on the chart over time.

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50 Years of Data Science

David Donoho

Department of Statistics, Stanford University, Standford, CA

ABSTRACT
More than 50 years ago, John Tukey called for a reformation of academic statistics. In "The Future of Data Analysis," he pointed to the existence of an as-yet unrecognized *science*, whose subject of interest was learning from data, or "data analysis." Ten to 20 years ago, John Chambers, Jeff Wu, Bill Cleveland, and Leo Breiman independently once again urged academic statistics to expand its boundaries beyond the classical domain of theoretical statistics; Chambers called for more emphasis on data preparation and presentation rather than statistical modeling; and Breiman called for emphasis on prediction rather than inference. Cleveland and Wu even suggested the catchy name "data science" for this envisioned field. A recent and growing phenomenon has been the emergence of "data science" programs at major universities, including UC Berkeley, NYU, MIT, and most prominently, the University of Michigan, which in September 2015 announced a $100M "Data Science Initiative" that aims to hire 35 new faculty. Teaching in these new programs has significant overlap in curricular subject matter with traditional statistics courses; yet many academic statisticians perceive the new programs as "cultural appropriation." This article reviews some ingredients of the current "data science moment," including recent commentary about data science in the popular media, and about how/whether data science is really different from statistics. The now-contemplated field of data science amounts to a superset of the fields of statistics and machine learning, which adds some technology for "scaling up" to "big data." This chosen superset is motivated by commercial rather than intellectual developments. Choosing in this way is likely to miss out on the really important intellectual event of the next 50 years. Because all of science itself will soon become data that can be mined, the imminent revolution in data science is not about mere "scaling up," but instead the emergence of scientific studies of data analysis science-wide. In the future, we will be able to predict how a proposal to change data analysis workflows would impact the validity of data analysis across all of science, even predicting the impacts field-by-field. Drawing on work by Tukey, Cleveland, Chambers, and Breiman, I present a vision of data science based on the activities of people who are "learning from data," and I describe an academic field dedicated to improving that activity in an evidence-based manner. This new field is a better academic enlargement of statistics and machine learning than today's data science initiatives, while being able to accommodate the same short-term goals. *Based on a presentation at the Tukey Centennial Workshop, Princeton, NJ, September 18, 2015.*

JOURNAL OF RESEARCH ON EDUCATIONAL EFFECTIVENESS
2019, VOL. 12, NO. 4, 570–593
https://doi.org/10.1080/19345747.2019.1658835

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METHODOLOGICAL STUDIES

Reshaping the Arc of Quantitative Educational Research: It's Time to Broaden Our Paradigm

Judith D. Singer[a]

ABSTRACT
The arc of quantitative educational research should not be etched in stone but should adapt and change over time. In this article, I argue that it is time for a reshaping by offering my personal view of the past, present and future of our field. Educational research—and research in the social and life sciences—is at a crossroads. There are many reasons for this, but chief among them is the rapid rise of data science, which has implications for educational research in general and SREE in particular. I ask us to question whether our laser focus on causal inference—which will remain crucially important—has crowded out other methods for studying equally important—yet not necessarily causal—questions. After introducing the wisdom of four muses—two philosophers of science and two statisticians—I sketch my personal research trajectory and its intersection with the field's. The remainder of the article describes three types of studies that I would like to see more of: longitudinal studies using truly longitudinal analyses; assessment and measurement studies; and studies using data science methods.

KEYWORDS
causal inference
data science
longitudinal analysis
assessment and measurement
machine learning

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The Data Science Common Task Framework (CTF):

1. Open large-scale real-world deidentified datasets
2. A Shared Culture of Shared Code for Shared Research
3. “Frictionless reproducibility” (Donoho, 2024)

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Open Access Large-Scale
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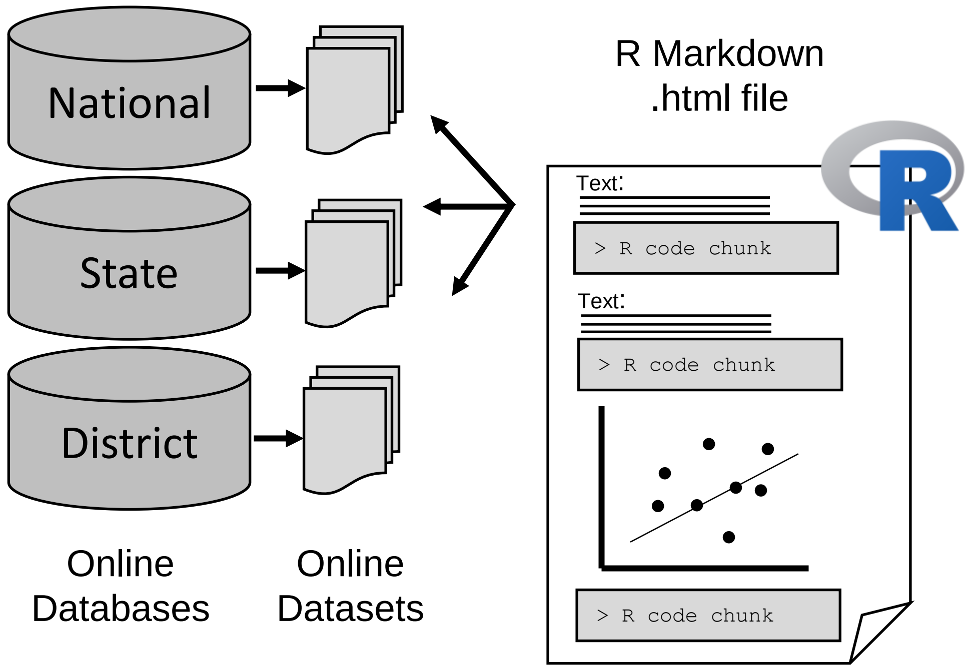

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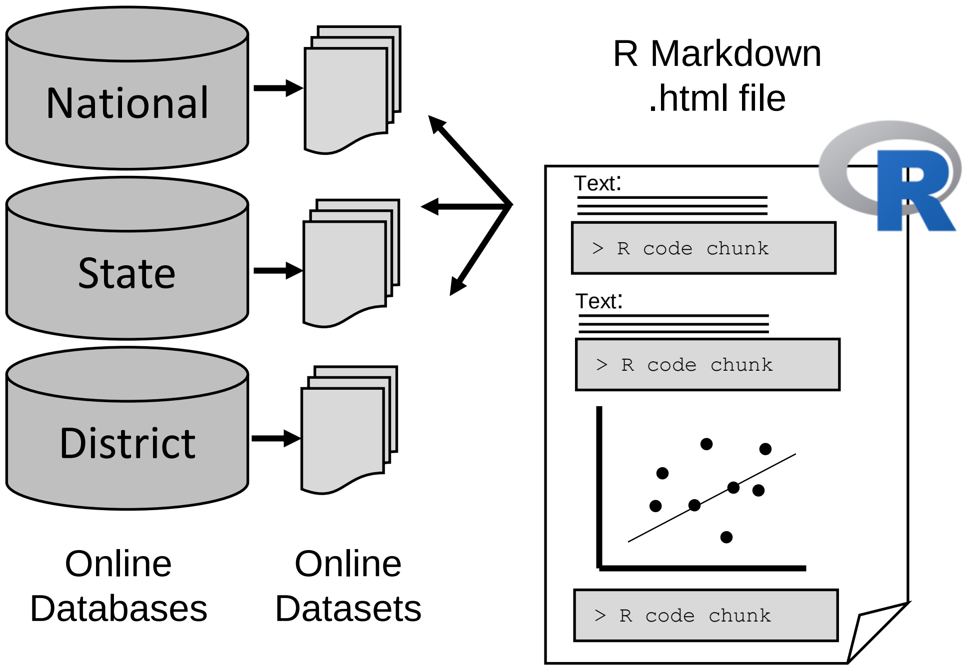
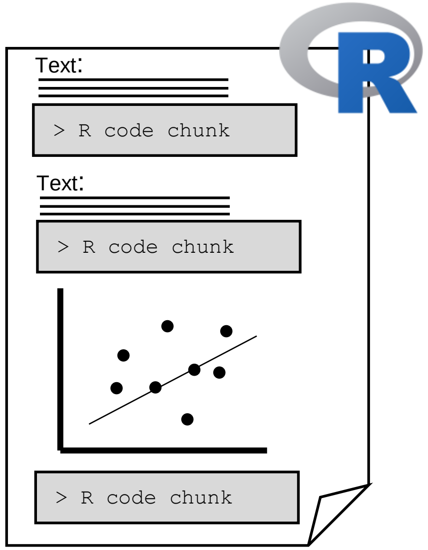


R Markdown

- .html that anyone can open in a browser
- All code provided. No hidden analysis.
- All data files import by URL
- No hidden data cleaning
- All analysis code included
- All visualization code included
- No C:\Bowers\workingdirectory\
- Copy/paste low-code/no-code replication
- Publish .html markdown as online appendix

Copy/Paste Replication

Allows anyone to copy/paste replicate and extend, through using open access public data and open access software. Democratizes the data and incentivizes replication, iteration, and crowdsourcing of solutions with stakeholder’s own data.



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Mapping 16 Equity Indicators to Open Public Education Indicator Data across 7 States, New York City and Washington DC

2022 NYC Report

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2023 *Educational Researcher*

Building School Data Equity, Infrastructure, and Capacity Through FAIR Data Standards: Findable, Accessible, Interoperable, and Reusable

Alex J. Bowers[1] and Yeonsoo Choi[1]

Despite increasing calls to build equitable data infrastructures, the education field has yet to have a shared guideline around equitable education data management and stewardship. To address this gap, we propose one framework from the data governance literature: the FAIR (Findable, Accessible, Interoperable, Reusable) data management principles complemented by the CARE (Collective benefits, Authority to control, Responsibility, Ethics) principles. We argue that making education data Findable, Accessible, Interoperable, and Reusable (FAIR) is a matter of equity and central to equity-focused data reuse. We illustrate the importance of FAIR education data by synthesizing our research experience and literature at the intersection of data governance and equity-focused data use.

Keywords: administration; assessment; data-driven decision-making; data governance; data life cycle; data management; data management principles; data standards; data systems; databases; data use; descriptive analysis; education data; educational policy; equity; leadership; school district research; state longitudinal data systems

Introduction

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2024 Principal Magazine

Tracking the Indicators of Opportunity

Use data to measure the intangibles that can contribute to educational equity

BY ALEX J. BOWERS, DANIELLA MOLLE, YEONSOO CHOI, AND RICHARD HALVERSON

Traditionally, educators have used data analysis to help identify gaps in outcomes across student demographic, racial, and socioeconomic groups. But using data to find gaps in achievement and behavioral outcomes says little about the underlying conditions that produce such gaps. Researchers such as Rochelle Gutiérrez call this narrow focus "gap-gazing."

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2025 Report: 7 States & DC

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Authors:
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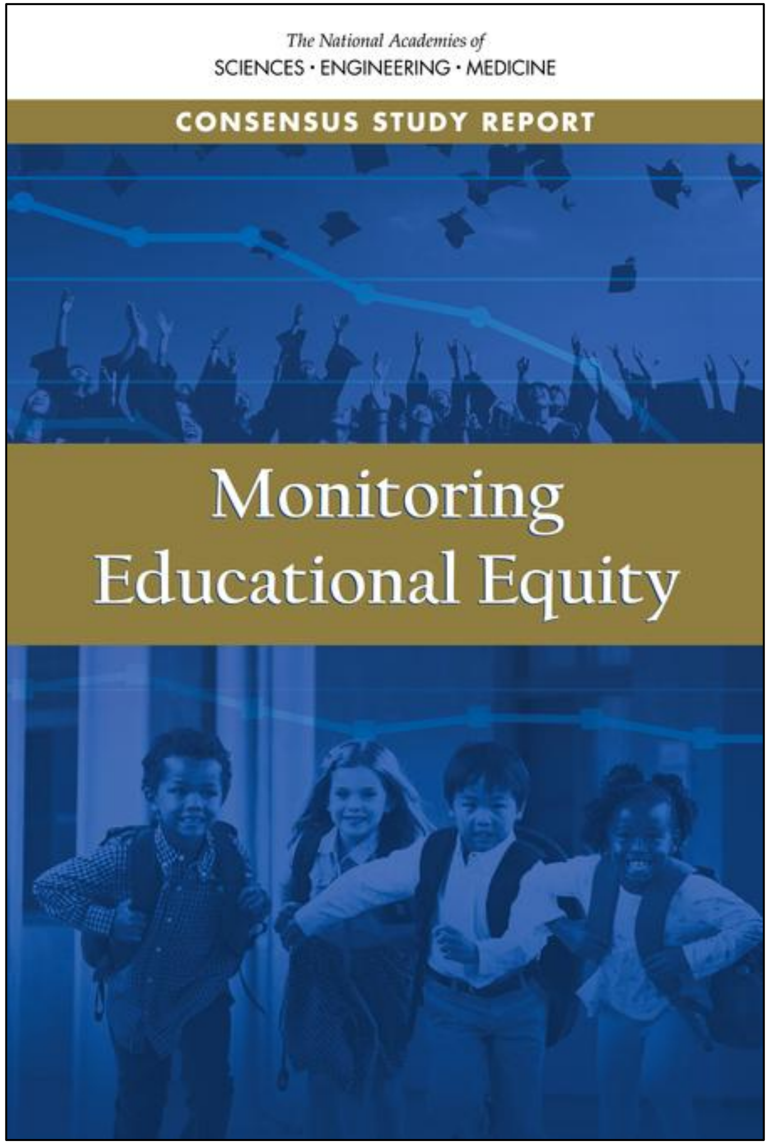
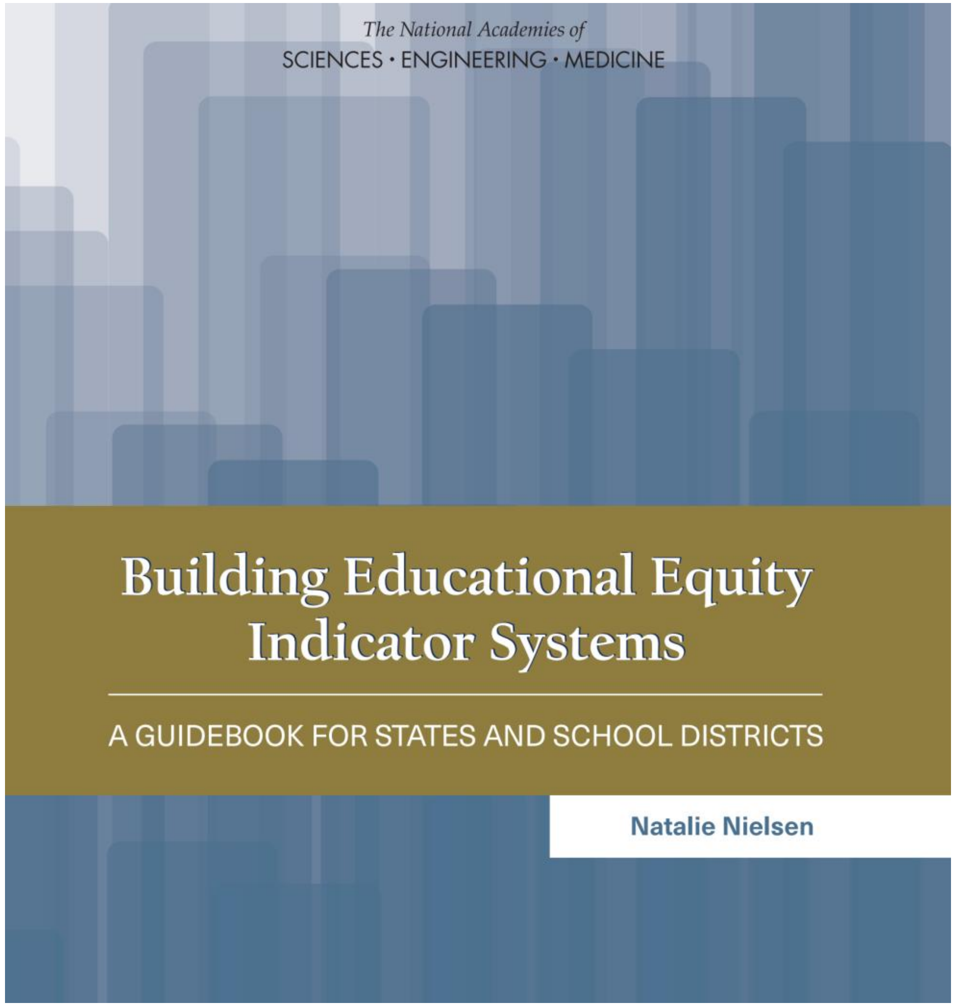
National Academies of Sciences, Engineering, and Medicine 16 Education Indicators (2019, 2020)



National Academies of Sciences, Engineering, and Medicine 2019. Monitoring Educational Equity. Washington, DC: The National Academies Press. https://doi.org/10.17226/25389



National Academies of Sciences, Engineering, and Medicine 2020. Building Educational Equity Indicator Systems: A Guidebook for States and School Districts. Washington, DC: The National Academies Press. https://doi.org/10.17226/25833

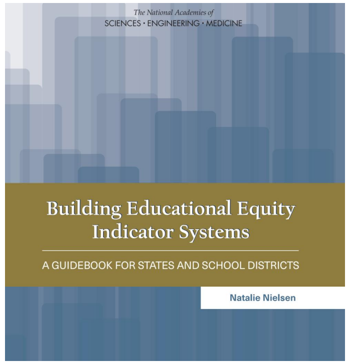
NASEM 16 Education Indicators: Going Beyond Outcomes to Examine Opportunities and Resources

<u>Pre-K:</u>

1. Academic Readiness
2. Self-Regulation and Attention Skills
3. Access to and Participation in High-Quality Pre-K Programs.

<u>K-12:</u>

4. Access to Effective Teaching.
5. Access to Rigorous Coursework.
6. Curricular Breadth.
7. Access to High-Quality Academic Supports.
8. Exposure to Racial and Economic Segregation.
9. School Climate.
10. Non-Exclusionary Disciplinary Practices.
11. Access to Non-Academic Supports for Student Success.
12. Engagement in Schooling.
13. Performance in Coursework.
14. Performance on Tests.
15. Educational Attainment - On-Time Graduation.
16. Educational Attainment – Post-Secondary Readiness.



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Education Level	Indicators of Disparities	What to Measure	Part of Required Federal Reporting?
Pre-K Education	Access to and participation in high-quality pre-K programs (opportunity)	Group differences in availability of and participation in licensed pre-K programs	No
	Academic readiness (outcome)	Group differences in reading, literacy, numeracy, and math skills	No
	Self-regulation and attention skills (outcome)	Group differences in self-regulation and attention skills	No
K-12 Education	Access to effective teaching (opportunity)	Group differences in exposure to novice, experienced, and certified teachers Racial and ethnic diversity of the teaching force	Partly
	Access to rigorous course-work (opportunity)	Group differences in availability of and enrollment in advanced, rigorous coursework; Advanced Placement, International Baccalaureate, and dual enrollment programs; and gifted and talented programs	Yes
	Curricular breadth (opportunity)	Group differences in availability of and enrollment in coursework in the arts, social sciences, sciences, technology, and world languages	No
	Access to high-quality academic supports (opportunity)	Group differences in access to and participation in formalized systems of tutoring or other types of academic supports, including special education services and services for English learners	No
	Students' exposure to racial, ethnic, and economic segregation (opportunity)	Group differences in exposure to concentrated poverty in schools Extent of racial segregation within and across schools	Partly
	School climate (opportunity)	Group differences in access to strong climates, as measured by perceptions of safety, academic support, academically focused culture, and teacher-student trust	No
	Nonexclusionary discipline practices (opportunity)	Group differences in out-of-school suspensions and expulsions	Yes
	Nonacademic supports for student success (opportunity)	Group differences in supports for emotional, behavioral, mental, and physical health	Yes
	Engagement in schooling (outcome)	Group differences in school attendance, absenteeism, and academic engagement	Partly
	Performance in coursework (outcome)	Group difference in success in classes, accumulating credits, grades, and grade point averages (GPAs)	Yes
	Performance on tests (outcome)	Group differences in achievement levels and learning growth in reading, math, and science	Yes
Educational Attainment	On-time graduation (outcome)	Group differences in on-time graduation	Yes
	Postsecondary readiness (outcome)	Group differences in enrollment in college, entry into the workforce, or enlistment in the military	Partly

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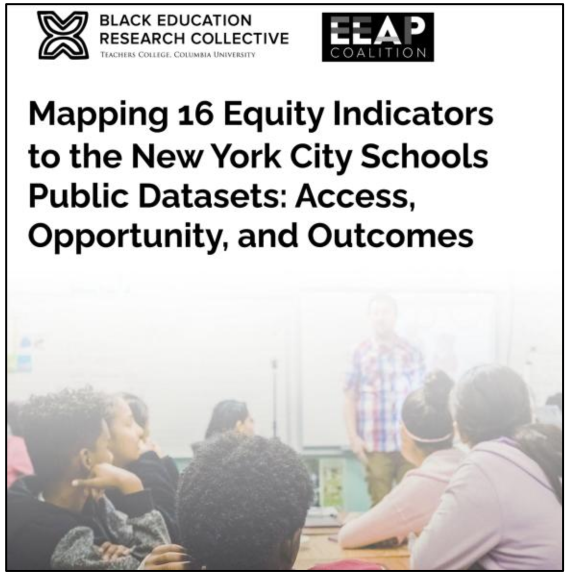
2022 NYC Report



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Keywords: administration; assessment; data-driven decision-making; data governance; data life cycle; data management; data management principles; data standards; data systems; databases; data use; descriptive analysis; education data; educational policy; equity; leadership; school district research; state longitudinal data systems

Introduction

Spurred by federal regulations concerning accountability systems and education data collection, pre-K–12 education agencies now collect and publish more data than ever before. A notable shift in recent data collection programs is the inclusion of equity measures (National Academies of Sciences, Engineering, and Medicine [NASEM], 2019, 2020) beyond traditional accountability metrics, such as standardized test scores. For example, the Every Student Succeeds Act (ESSA) requires states to include at least one nonacademic measure of school quality and student success when creating accountability systems (Ni et al., 2016; Temkin et al., 2021). Simultaneously, increased attention to data has led to growing interest in how to effectively manage and share education data for the purpose of data-driven decision-making (Bloom-Weltman et al., 2021; Mandinach & Schildkamp, 2021). This interest is evident in the development of statewide longitudinal data systems (SLDSs) and the increasing call to implement data management standards to enable reusing and sharing data among various entities (Hall & Huennekens, 2016). States and districts have also started to publish education data in various formats, such as school dashboards, to not only inform community stakeholders but also enable their participation in school improvement (Bowers, 2021a).

Given these recent developments, many have called for the need to center equity across education data systems and infrastructures (Bowers, 2021b; Ishimaru et al., 2022). Researchers have urged to move beyond analyzing group differences in educational outcomes and to operationalize various dimensions of equity, such as access to educational resources and opportunities (Welner & Carter, 2013), and publicly report equity indicators (NASEM, 2019). As defined by the National Academies of Sciences, Engineering, and Medicine (NASEM; 2019, p. 1):

> The purpose of such indicators is not to track progress toward aggregate goals, such as that all students graduate high school within 4 years of entering 9th grade, but to identify differences in progress toward that goal, differences in students' family background and other characteristics, and differences in the

[1]Teachers College, Columbia University, USA

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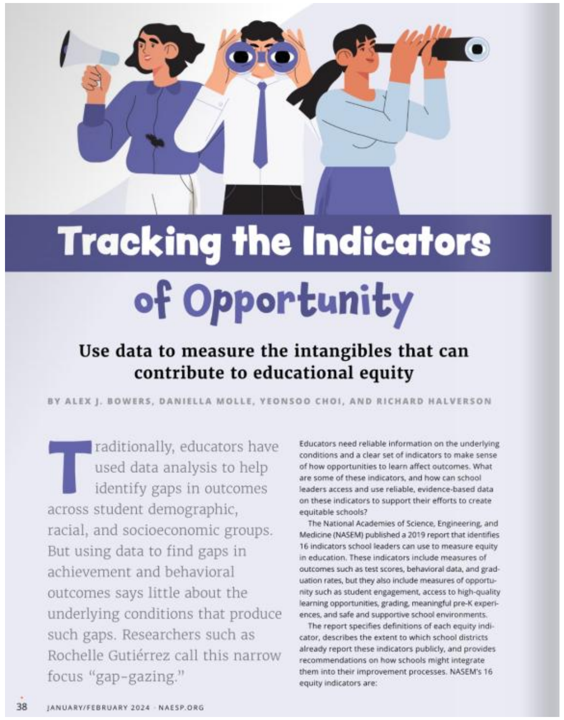
2024 Principal Magazine



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Use data to measure the intangibles that can contribute to educational equity

BY ALEX J. BOWERS, DANIELLA MOLLE, YEONSOO CHOI, AND RICHARD HALVERSON

Traditionally, educators have used data analysis to help identify gaps in outcomes across student demographic, racial, and socioeconomic groups. But using data to find gaps in achievement and behavioral outcomes says little about the underlying conditions that produce such gaps. Researchers such as Rochelle Gutiérrez call this narrow focus "gap-gazing."

Educators need reliable information on the underlying conditions and a clear set of indicators to make sense of how opportunities to learn affect outcomes. What are some of these indicators, and how can school leaders access and use reliable, evidence-based data on these indicators to support their efforts to create equitable schools?

The National Academies of Science, Engineering, and Medicine (NASEM) published a 2019 report that identifies 16 indicators school leaders can use to measure equity in education. These indicators include measures of outcomes such as test scores, behavioral data, and graduation rates, but they also include measures of opportunity such as student engagement, access to high-quality learning opportunities, grading, meaningful pre-K experiences, and safe and supportive school environments.

The report specifies definitions of each equity indicator, describes the extent to which school districts already report these indicators publicly, and provides recommendations on how schools might integrate them into their improvement processes. NASEM's 16 equity indicators are:

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Bowers et al. (2024) Tracking the Indicators of Opportunity. *Principal Magazine*, NAESP, Vol 103(3) Jan/Feb, p.38-39. https://www.naesp.org/resource/tracking-the-indicators-of-opportunity/

2025 Report: 7 States & DC

Mapping Public Open Access K-12 State Education Indicator Data Across 7 States and Washington D.C. Using the FAIR Data Principles

Authors:
Alex J. Bowers, Yeonsoo Choi, Yingqi Huan, Yanxing Huang, Jingjing Jiang, Ghipsel Cibrian Lopez, Alyssa Murdoch, Kecen Pu, Maeghan Sill, Jonathan Williams, Yue Summer Wu, Guoliang Xu, Christopher Saldaña, Richard Halverson

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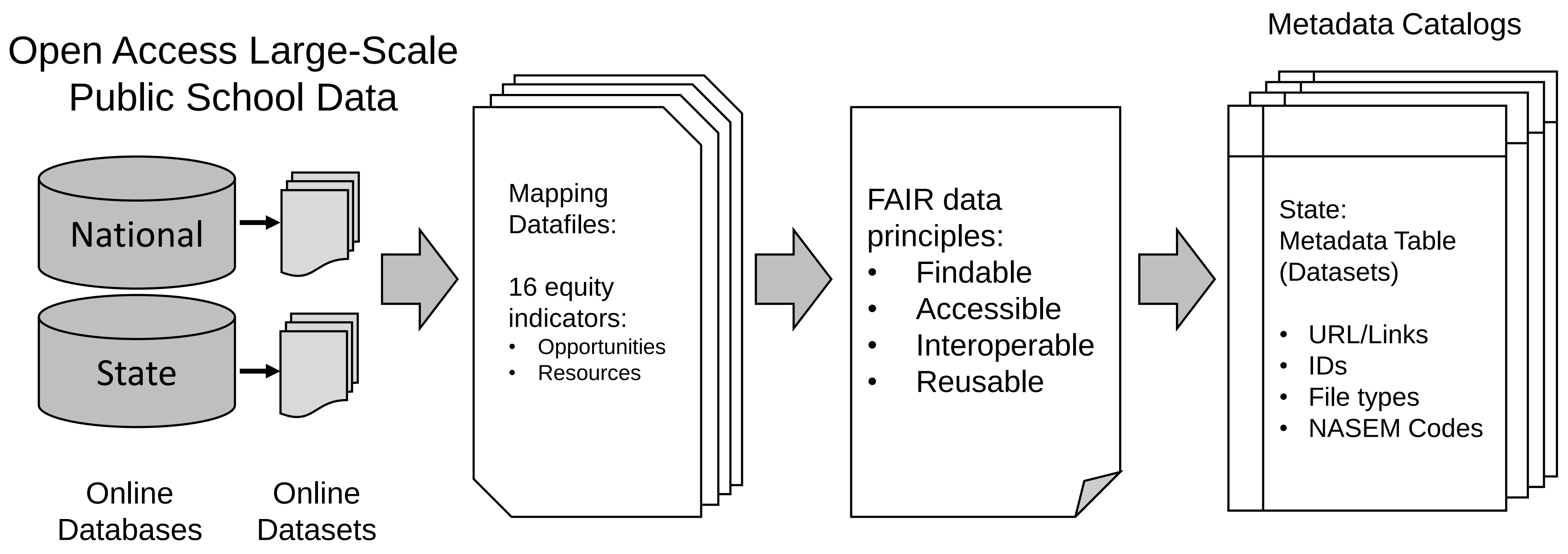
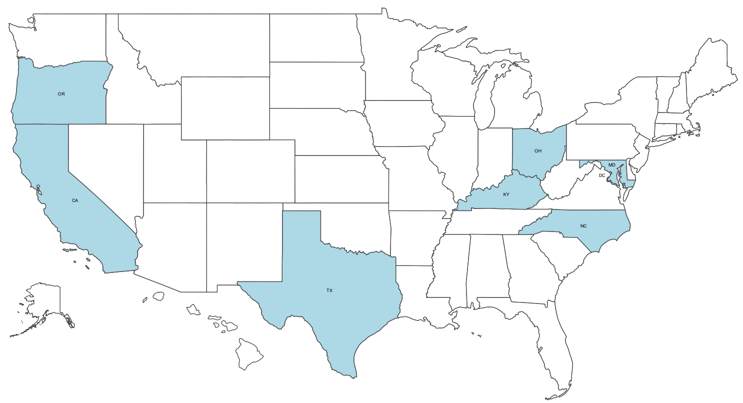
Mapping the Universe of Public Open Access PK-12 Education and Finance Data Across 7 States and Washington DC to the NASEM 16 Equity Indicators and the Global FAIR Data Principles





<u>7 States and DC:</u>

1. California
2. Kentucky
3. Maryland
4. North Carolina
5. Oregon
6. Ohio
7. Texas
8. Washington DC

- NASEM 16 Equity Indicators Datafiles: n=3,822

Mapping Public Open Access K–12 State Education Indicator Data Across 7 States and Washington, D.C. Using the FAIR Data Principles

- Mapped the universe of open public data to the National Academies of Science, Engineering, and Medicine's (NASEM) 16 equity indicators for schools across 7 states and DC including:
- California, Kentucky, Maryland, North Carolina, Ohio, Oregon, Texas, Washington DC.
- Analyzed with the global FAIR data principles of Findable, Accessible, Interoperable, and Reuseable
- Two independent raters opened each datafile and coded it to the NASEM 16 equity indicators, providing a full interrater reliability analysis.

Main Findings:

1. <u>The data are vast</u>: We identified **3,822 individual datafiles** across the 7 states and DC, with most states having all 16 of the NASEM equity indicators.
2. <u>Challenges with FAIR</u>: We detail a large range of challenges across this sample of states in making their data Findable, Accessible, Interoperable, and thus Reusable (FAIR).
3. <u>Interoperable Metadata Catalogs</u>: We leave the data "at rest" on the state websites and created an open access metadata layer in .csv files that provides the links to each datafile URL, codebooks, school merge ID, and our qualitative coding and interrater reliability analysis for each of the 3,822 datafiles.
4. <u>Empirically validating NASEM 16 Equity Indicators</u>: We empirically validate the extent to which the NASEM 16 equity indicators exist at a factor analytic level using the actual datasets that states post with an interrater reliability analysis.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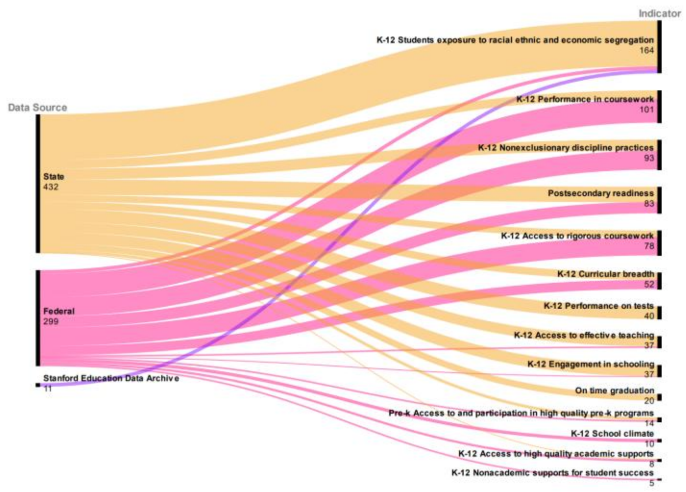
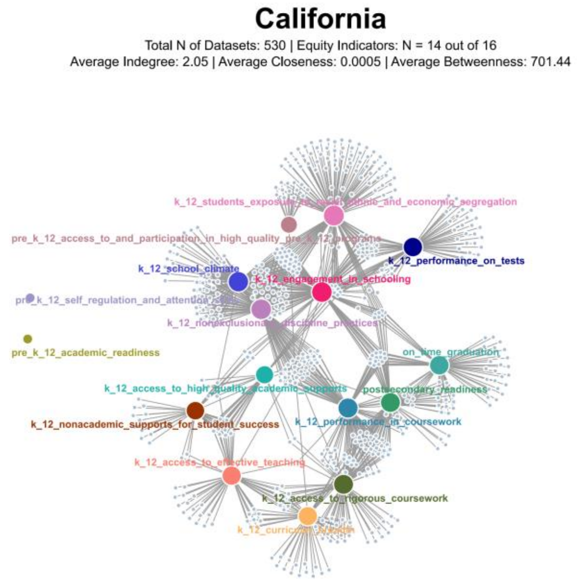
Data Availability by NASEM Indicator Domains: Cross-locale Examination

		State/Local Government							
		CA	OH	TX	NC	DC	KY	MD	OR
Access	Racial, ethnic, and economic segregation	**4**	**4**	**4**	**4**	**4**	**4**	**4**	**4**
	High-quality pre-K programs	**4**	**4**	**4**	**4**	**4**	**4**	**4**	**4**
	Effective teaching	**4**	**4**	**4**	3	**4**	**4**	3	**4**
	Rigorous coursework	**4**	**4**	**4**	**4**	**4**	**4**	**4**	**4**
	Curricular breadth	**4**	**4**	**4**	**4**	**4**	**4**	**4**	**4**
	High-quality academic supports	**4**	**4**	**4**	**4**	**4**	**4**	**4**	**4**
	School climate	**4**	**4**	**4**	**4**	**4**	**4**	**4**	**4**
	Nonexclusionary discipline practices	**4**	**4**	**4**	**4**	**4**	**4**	**4**	**4**
	Nonacademic supports	3	3	**4**	3	**4**	3	3	3
Outcome	Pre-k academic readiness		3	**4**	3		**4**	3	**4**
	Pre-k self-regulation and attention skills		3	**4**	3		**4**	3	**4**
	Engagement in schooling	**4**	**4**	**4**	**4**	**4**	**4**	**4**	**4**
	Performance in coursework	**4**	**4**	**4**	**4**	**4**	**4**	**4**	**4**
	Performance on tests	**4**	**4**	**4**	**4**	**4**	**4**	**4**	**4**
	On-time graduation	**4**	**4**	**4**	**4**	**4**	**4**	3	**4**
	Postsecondary readiness	**4**	**4**	**4**	**4**	**4**	**4**	**4**	**4**
N of NASEM Indicators		14	16	16	16	14	16	16	16
N of Disaggregated NASEM Indicators		13	13	16	12	14	15	11	15
Total Number of State Datafiles		313	444	812	267	278	560	476	455
Total Number of Federal Datafiles		217	217	217	217	217	217	217	217

Figure 64

Alluvial Plot of Sources of Data Mapped to NASEM Indicators for California





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Note. In our coding system, 3 denotes datasets containing direct measures per NASEM's definition without demographic breakdown, and 4 indicates direct measures with demographic disaggregation

Partnering with School Leaders: Equity Indicator Data Collaborative Workshop 2025

How Data Can Create More Equitable Schools

A data collaborative workshop hosted by TC's Alex Bowers teaches school leaders how to leverage data to better promote equity

+1 +1 +1 +1

https://www.tc.columbia.edu/articles/2025/august/how-data-can-create-more-equitable-schools/

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Mapping Public Open Access K–12 State Education Indicator Data Across 7 States and Washington, D.C. Using the FAIR Data Principles - *Explore the data yourself!*

Full Report Download:

Bowers, A. J., Choi, Y., Huan, Y., Huang, Y., Jiang, J., Cibrian Lopez, G., Murdoch, A., Pu, K., Sill, M., Williams, J., Wu, Y. S., Xu, G., Saldaña, C., & Halverson, R. (2025). Mapping Public Open Access K–12 State Education Indicator Data Across 7 States and Washington, D.C. Using the FAIR Data Principles. Teachers College, Columbia University. https://doi.org/10.7916/c0jk-5e64

State FAIR-Aligned Metadata Catalogs:

- Appendix 1 California metadata catalog: https://doi.org/10.7916/jqkg-2j17
- Appendix 2 Kentucky metadata catalog: https://doi.org/10.7916/8gj9-ce21
- Appendix 3 Maryland metadata catalog: https://doi.org/10.7916/gn8t-dp57
- Appendix 4 North Carolina metadata catalog: https://doi.org/10.7916/mr7d-zc90
- Appendix 5 Ohio metadata catalog: https://doi.org/10.7916/wv0f-jq15
- Appendix 6 Oregon metadata catalog: https://doi.org/10.7916/wgbv-mx11
- Appendix 7 Texas metadata catalog: https://doi.org/10.7916/1hx6-9013
- Appendix 8 Washington DC metadata catalog: https://doi.org/10.7916/zzfq-7212

Data Dictionary and Full Interrater Reliability Data and Coding Notes:

- Appendix 9 MDMT Data Dictionary: https://doi.org/10.7916/ydwn-1s20
- Appendix 10 Interrater Reliability data: https://doi.org/10.7916/0bv2-zm35

Analysis Copy/Paste Replication .html R Markdowns:

- Appendix 11 Dataset Social Network Analysis R Markdown: https://doi.org/10.7916/9m7q-sq86
- Appendix 12 Interrater Reliability R Markdown: https://doi.org/10.7916/3vny-6b48

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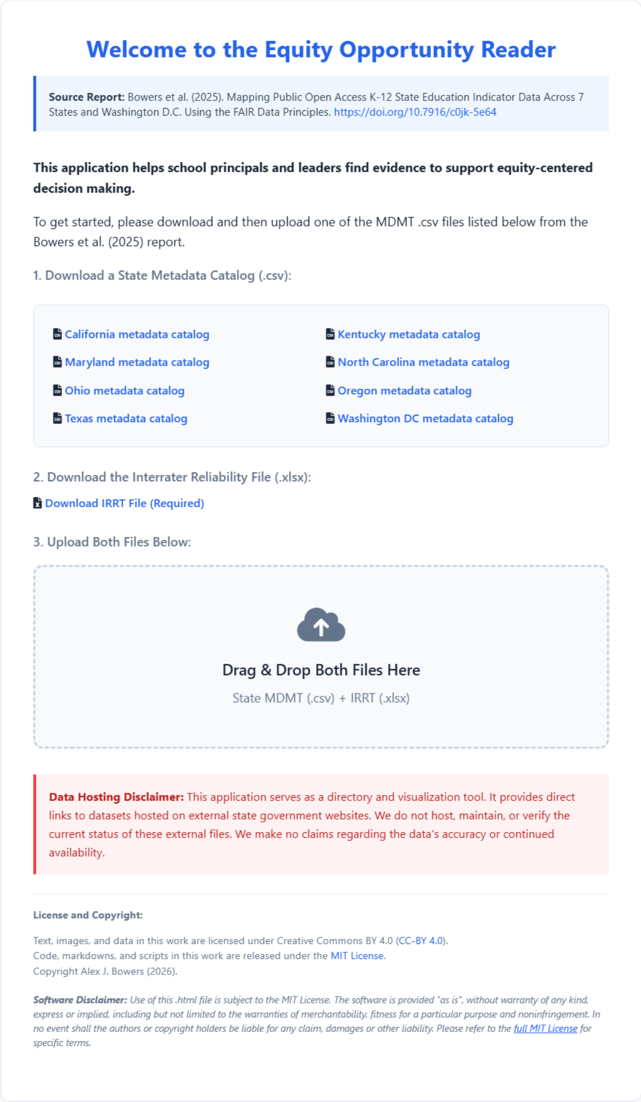
SDP First Look! Preview of the Alpha Build of the: Principal Evidence Connector/Equity Opportunity Reader

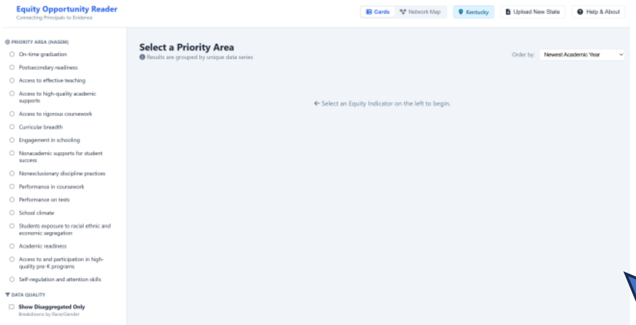
Please Note:

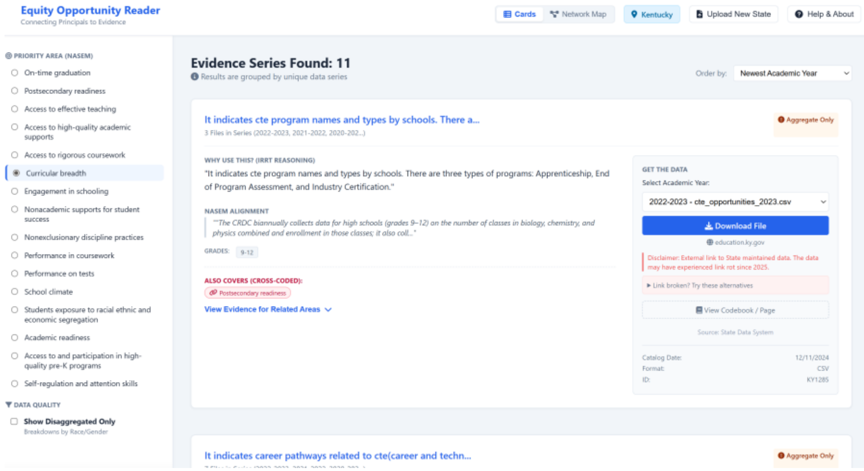
1. **Please do not distribute, forward, or post online.**
2. This .html file is in alpha testing. Help test it today!
3. We plan to hopefully release it fully by summer 2026.

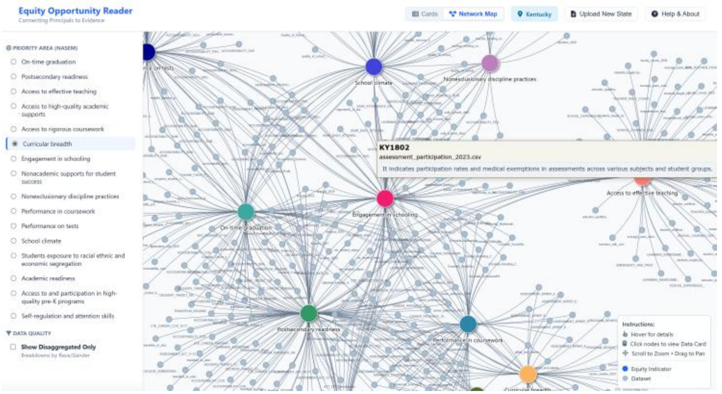
4. Gdrive Link: Principal System Evidence Connector V1-40.html
5. https://drive.google.com/file/d/1MTTMbZYj1pGlj-lqBCxcsI12FB1IKBoW/view?usp=sharing

6. First download the file and then open in a browser.
7. Works best in Chrome. California or Kentucky are good place to start









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For the next few minutes on your own or in teams:

1. Download and begin to explore the report or metadata catalogs.
   a) Feel free to download the .csv files and explore the report appendices
   b) Explore the .html markdowns. The Social Network Analysis markdown appendix 11 has interactive figures and all the code in R.
   c) Or: Test the pilot Evidence Connector .html app to view the metadata and download data. Best states to try at the start: California or Kentucky.

2. As you explore the metadata consider a few questions:
   a) How do we help state and district systems make the data FAIR and interoperable?
   b) Which opportunity indicators help us understand our outcome data?
   c) What improvements would we like to see, and how would these indicators help us measure the change?

3. After a few minutes we'll do a quick Q&A for this section.

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