

Why Visualize Health Data?

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INTRODUCTION

Health data is inherently complex, vast, and multi-dimensional. It encompasses individual-level biometrics, clinical encounters, and population-level indicators such as maternal mortality, disease burden, and vaccination coverage. The rapid expansion of data sources from electronic health records (EHRs) and genomic databases to mobile health applications and wearable sensors has significantly increased the challenge of synthesizing, interpreting, and communicating meaningful insights from health information (Rogers, 2019).

In this increasingly data-rich environment, data visualization has emerged as a critical tool for transforming complex datasets into understandable and actionable information. By converting raw data into charts, maps, dashboards, and other visual formats, visualization leverages human visual cognition to simplify complexity, reveal patterns, and support evidence-based decision-making. Consequently, visualizations serve not only as analytical tools but also as powerful instruments for communication, persuasion, and policy advocacy.

The importance of visualization is deeply rooted in the history of public health. One of the earliest and most influential examples is Dr. John Snow's cholera map of London in 1854, which enabled the identification of the Broad Street water pump as the source of a cholera outbreak and laid the foundation for modern epidemiology. Similarly, Florence Nightingale employed innovative radial diagrams to communicate mortality patterns during the Crimean War, thereby influencing healthcare reforms and improving sanitary conditions. As

Nightingale famously noted, her visualizations were designed to “*affect through the eyes what we fail to convey through their word-proof ears.*”

The historical evolution of health data visualization is illustrated in **Fig. 1**, which highlights key milestones ranging from nineteenth-century disease mapping to contemporary real-time public health dashboards.

Figure 1 illustrates major milestones in the history of health data visualization, including John Snow's cholera map (1854), Florence Nightingale's Coxcomb diagram (1858), and the Johns Hopkins University COVID-19 Dashboard (2020), highlighting the transition from static visual representations to real-time interactive analytics.

The timeline demonstrates the progression of visualization methods in public health from early analog approaches to modern digital platforms. It includes: (a) John Snow's cholera map (1854), which spatially identified the Broad Street pump as the source of infection; (b) Florence Nightingale's Coxcomb diagram (1858), which visually demonstrated patterns of battlefield mortality and influenced hospital reforms; and (c) the Johns Hopkins University COVID-19 Dashboard (2020), which enabled global, real-time visualization of pandemic trends and outcomes.

Together, these milestones illustrate how visual methods have continuously evolved to meet the communication, analytical, and decision-support needs of different public health eras. Today, data visualization continues to shape public health discourse through global dashboards tracking infectious diseases such as COVID-19 and malaria, as well as national monitoring platforms such as

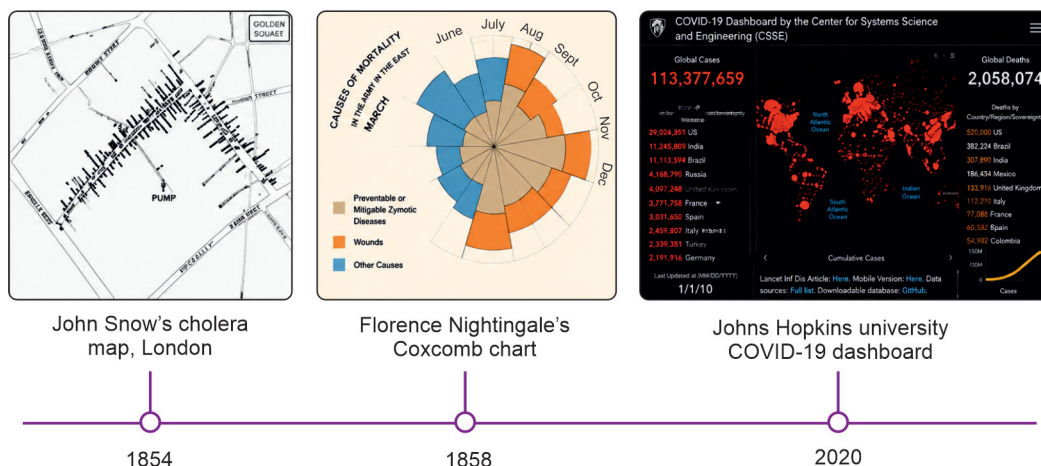


Fig. 1: Evolution of Health Data Visualization in Public Health

India's POSHAN Abhiyaan nutrition scorecards. These tools serve two fundamental purposes: (i) to make complex health data intelligible and actionable for diverse audiences, and (ii) to inform and influence health policies through compelling, evidence-based storytelling.

This chapter explores these core motivations and demonstrates how well-designed visualizations, whether exploratory or explanatory, are central to

strengthening twenty-first-century public health systems, improving data-driven decision-making, and enhancing the communication of scientific evidence.

The broader role of visualization across the analytical workflow is illustrated in **Fig. 2**, which highlights the progression from exploratory analysis to communication and dissemination.

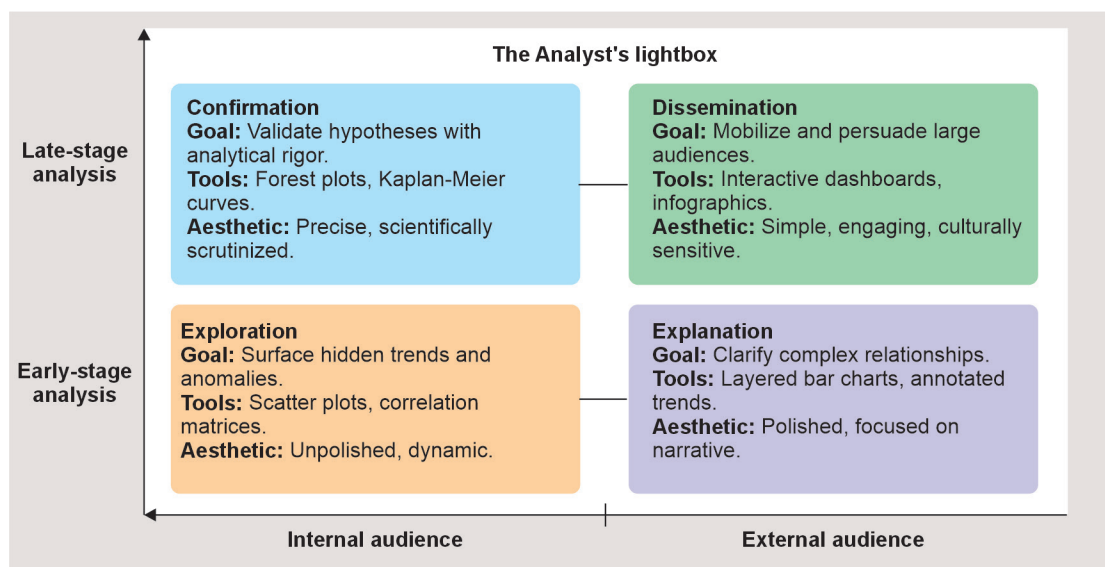


Fig. 2: The Analyst's Lightbox Illustrating the Progression of Visualization Across Analytical Stages and Audience Contexts, from Exploratory Analysis to Dissemination

COMMUNICATING COMPLEXITY WITH CLARITY

The Multilayered Nature of Health Data

Health data is inherently multidimensional. A single patient's digital health record may include demographic characteristics, clinical symptoms, diagnostic test results, treatment protocols, and outcomes captured across multiple time points and healthcare settings. When aggregated across populations, these attributes form complex, high-dimensional datasets that require sophisticated approaches for meaningful interpretation (Hripcsak *et al.*, 2015; Raghupathi & Raghupathi, 2014).

Conventional summaries such as spreadsheets or pivot tables can store and organize such information, but they often obscure subtle patterns, relationships, and trends. In contrast, data visualization enables rapid and intuitive understanding by leveraging the human brain's natural capacity for pattern recognition and visual processing (Ware, 2020; Few, 2009). By transforming numerical and categorical data into visual forms, researchers can more readily identify trends, outliers, clusters, and relationships that may otherwise remain hidden within large datasets.

For example, a Sankey diagram, commonly used to represent flows and proportional relationships, can effectively illustrate how patient groups transition across different stages of care. Such visualizations enable researchers, clinicians, and policymakers to identify critical points of attrition, disparities in service utilization, and variations in treatment pathways. By revealing how different demographic groups progress through healthcare systems and how these trajectories influence outcomes, Sankey diagrams provide valuable insights for health system planning and evaluation.

An example of this approach is presented in **Fig. 3**, which illustrates patient flows across multiple dimensions of healthcare delivery and outcomes.

Visualization as a Cognitive Tool

The human brain is inherently optimized for visual information processing. According to the dual-channel theory of learning (Mayer, 2005), cognitive processing occurs through two complementary pathways, visual and verbal, allowing individuals to interpret graphical information more efficiently than text alone. By distributing information across these channels, visualizations reduce cognitive load,

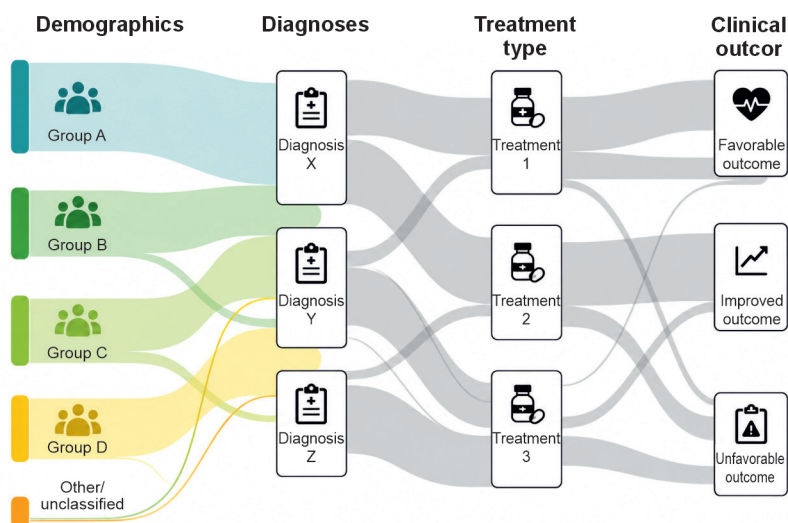


Fig. 3: Sankey diagram illustrating patient-level flows across healthcare pathways

enhance comprehension, and improve long-term retention, particularly in data-intensive fields such as health research.

Well-designed visualizations transform abstract numerical data into intuitive and accessible insights. Rather than navigating extensive tables of figures, users can rapidly identify patterns, trends, disparities, and outliers. This capability is especially critical in public health, where timely interpretation of evidence is essential for informed and inclusive decision-making.

The conceptual basis of this process is illustrated in **Fig. 4**, which demonstrates how visual and verbal pathways interact to transform raw data into actionable knowledge.

Illustrative examples include:

- A choropleth map displaying maternal mortality across districts enables immediate recognition of spatial disparities that may remain hidden in tabular presentations of the same data (Few, 2009).
- A time-series plot of daily COVID-19 cases reveals infection waves, policy impacts, and recovery trends more effectively than static numerical summaries, thereby facilitating rapid interpretation of evolving public health conditions (Dong *et al.*, 2020).

The practical advantages of visual representation over tabular presentation are demonstrated in **Fig. 5**, which compares two approaches to presenting anemia prevalence data.

This figure compares a tabular presentation of anemia prevalence with a graphical representation, demonstrating how visual formats reduce cognitive load and enable faster interpretation of patterns and disparities. By converting complex numerical information into visual form, trends, comparisons, and inequalities become more readily apparent to both technical and non-technical audiences.

A classic historical example is Florence Nightingale's Coxcomb Diagram, which illustrated military deaths by cause and month during the Crimean War. This innovative radial visualization communicated the urgency of sanitary reform far more effectively than textual reports or tabular summaries. Consequently, it functioned not only as an analytical tool but also as a powerful instrument of advocacy, contributing to significant reforms in British military healthcare (Tufte, 1983).

Lessons from Global Health Dashboards and COVID-19

The COVID-19 pandemic underscored the critical role of dashboards in translating rapidly evolving and complex datasets into actionable insights.

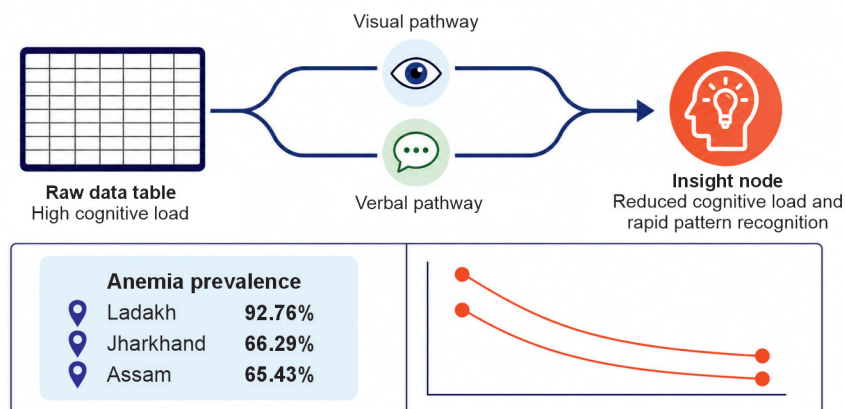


Fig. 4: Conceptual Model of Dual-Channel Cognitive Processing in Data Visualization, Illustrating How Visual and Verbal Pathways Transform Raw Data into Actionable Insight Through Reduced Cognitive Load and Enhanced Pattern Recognition

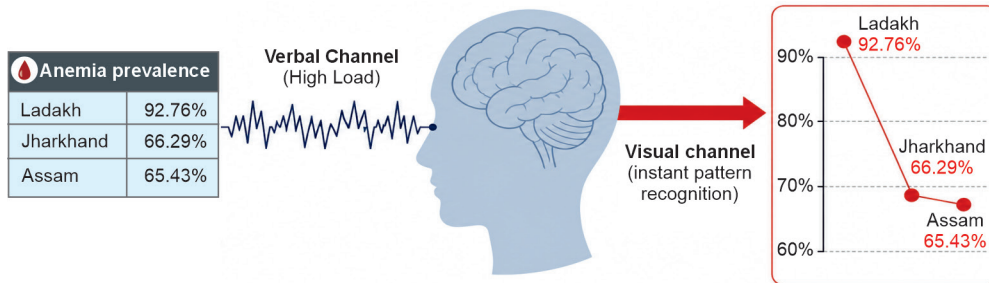


Fig. 5: Tabular Versus Visual Representation of Health Data (Anemia Prevalence Example)

Among the most influential examples was the Johns Hopkins University COVID-19 Dashboard, which became a global reference point by providing interactive maps, real-time case tracking, and cumulative mortality trends that shaped both public understanding and policy responses (Dong *et al.*, 2020).

At the national level, India's Ministry of Health and Family Welfare (MoHFW) disseminated granular state-level updates throughout the pandemic. Although more text-based in presentation, its status as the official source of COVID-19 statistics made it central to governance, public communication, and policy implementation. In parallel, international organizations such as the World Health Organization (WHO) employed heat maps, trend lines, and interactive dashboards to visualize malaria patterns and other public health indicators, thereby informing funding priorities, intervention strategies, and resource allocation.

A comparative overview of selected public health dashboards is presented in [Table 1](#), highlighting

differences in geographic scope, target audience, visual representation, and analytical strengths.

Similarly, national nutrition dashboards in India, particularly those developed under the POSHAN Abhiyaan, utilize data from the National Family Health Survey (NFHS-5) to generate interactive and policy-relevant visualizations. Beyond nutrition, NFHS-5 data also facilitate the exploration of emerging non-communicable disease risk factors and health inequalities across regions.

An example of such a visualization is presented in [Fig. 6](#), which displays the prevalence of mildly elevated blood pressure (systolic 140–159 mm Hg and/or diastolic 90–99 mm Hg) among men and women across selected districts of Bihar. The clustered bar chart clearly reveals gender-based disparities, with a consistently higher prevalence among men. Such patterns may remain difficult to identify in raw tabular datasets, underscoring the value of visualization in enhancing interpretability and supporting evidence-based public health decision-making.

Table 1: Comparative Overview of Major Public Health Dashboards

Dashboard	Geographic scope	Key visuals	Target audience	Strengths
JHU COVID-19 Dashboard	Global	Maps, time-series curves	Public, media, researchers	Real-time international updates
MoHFW India	National (India)	Tables, line charts	Bureaucrats, journalists	Official central data source
WHO Malaria Dashboard	Global/Regional	Heat maps, trend lines	Funders, policymakers	Strong geographic and temporal insights
POSHAN/Nutrition Dashboard	National/District	Clustered bar charts	Program managers, NGOs	Highlights gender and district-level disparities

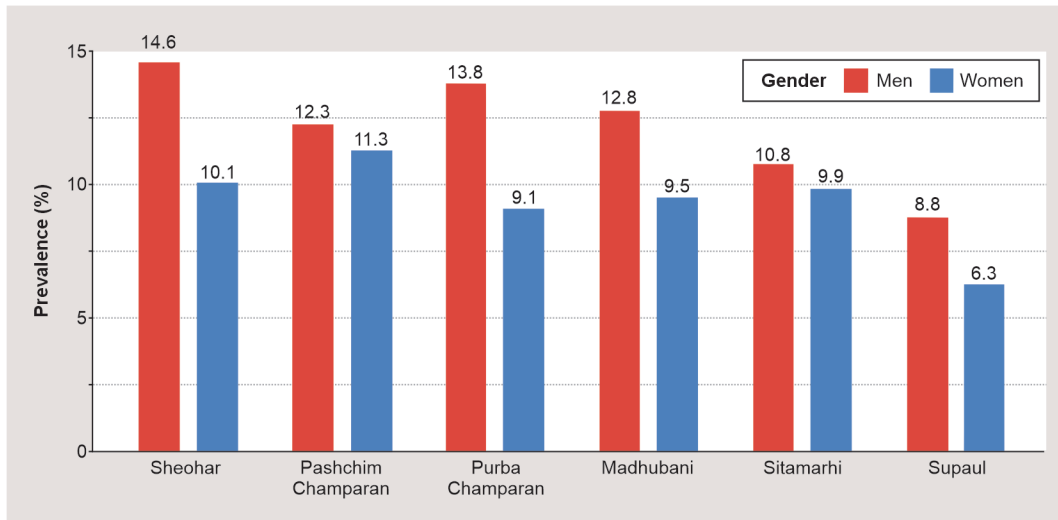


Fig. 6: Prevalence of Mildly Elevated Blood Pressure (Systolic 140–159 mm Hg and/or Diastolic 90–99 mm Hg) among Men and Women across Selected Districts of Bihar

Theoretical Foundations of Visualization

The design of effective data visualizations is guided by both aesthetic and analytical principles. Edward Tufte (1983) argued that well-crafted graphics should convey “the greatest number of ideas in the shortest time with the least ink.” This principle emphasizes minimalism by eliminating unnecessary visual elements and focusing attention on structure, patterns, and meaning. Similarly, Stephen Few (2009) stressed that clarity and accuracy must take precedence over decorative effects, particularly when visualizations are used to inform public health decisions. Complementing these perspectives, Kosslyn (2006) emphasized that effective graph design should be audience-centered, ensuring that visual displays facilitate accurate interpretation while minimizing cognitive effort.

In practice, health researchers must balance two complementary types of visualizations:

Exploratory Graphics: These visualizations are used during the analytical process to identify patterns, anomalies, clusters, and outliers. For example, a scatterplot of tuberculosis (TB) incidence versus vaccination coverage may reveal correlations or unexpected deviations across districts that warrant further investigation.

Explanatory Graphics: These visualizations are refined for communication with policymakers, stakeholders, healthcare professionals, or the general public. For instance, a bar chart showing annual TB case counts by age group, annotated with key interventions, can present a clear and actionable narrative.

Effective visualization in public health depends on successfully transitioning from exploratory insight to explanatory clarity, ensuring that complex datasets are translated into meaningful, evidence-based decisions.

This distinction between exploratory and explanatory visualization is illustrated in **Fig. 7**, which presents examples of both approaches using tuberculosis-related data.

The emergence of web-based visualization frameworks such as D3.js (Bostock *et al.*, 2011) and Vega-Lite (Heer *et al.*, 2010) has significantly transformed the visualization of health data. These platforms enable the creation of interactive, scalable, and reproducible graphics that respond dynamically to user input, thereby enhancing both engagement and transparency. For example, policymakers can interact with maps to explore real-time immunization coverage, examine district-

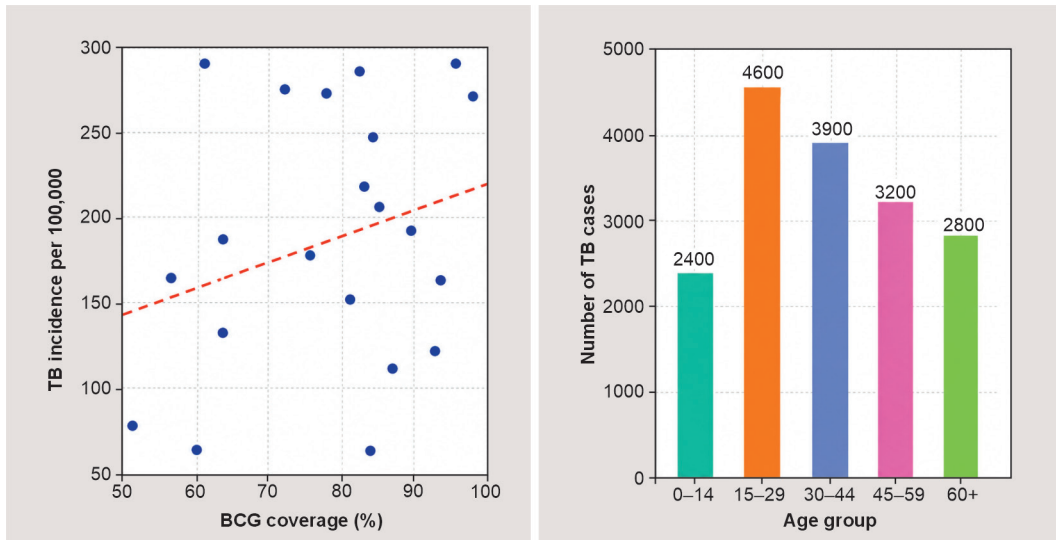


Fig. 7: Side-by-Side Comparison of an Exploratory Scatterplot and an Explanatory Bar Chart, Both Illustrating Tuberculosis Trends Across Indian States (2016–2022)

level disparities, and access contextual information that supports evidence-based decision-making.

As visualization technologies continue to evolve, grounding their application in strong theoretical principles remains essential. Regardless of whether visualizations are static or interactive, effective design should prioritize clarity, accessibility, accuracy, transparency, and ethical communication. These principles ensure that visualizations not only convey information effectively but also support informed public health action.

VISUALS IN POLICY AND ETHICS

Visuals as Catalysts for Action

In the realm of health policy, visualizations often possess greater persuasive power than complex statistical models. Policymakers, frequently operating under time constraints and without specialized technical training, rely on clear and intuitive visual representations to support decision-making. A simple bar chart demonstrating a rise in tuberculosis incidence within a specific district may prompt more immediate attention and response than multiple pages of regression outputs or confidence intervals.

Well-designed visualizations have the capacity to transform abstract inequities into urgent moral and political priorities. By making disparities visible, understandable, and actionable, they bridge the gap between evidence and intervention. A notable example is provided by the Lancet Commission on Global Surgery (Meara *et al.*, 2015), which employed a compelling global map to illustrate the “five billion gap”, the estimated number of people lacking access to safe, affordable, and timely surgical care worldwide. Presented alongside clear geographic comparisons, this visualization translated a complex global health issue into a powerful and accessible narrative.

Such visual evidence not only enhanced comprehension but also galvanized policy attention, reframing surgical care from a specialized medical service to a fundamental component of health equity and universal health coverage.

This example is illustrated in **Fig. 8**, which highlights global disparities in access to surgical care.

Such examples demonstrate that effective visualizations do more than communicate information; they influence agendas, shape public discourse, and support evidence-informed policy action.

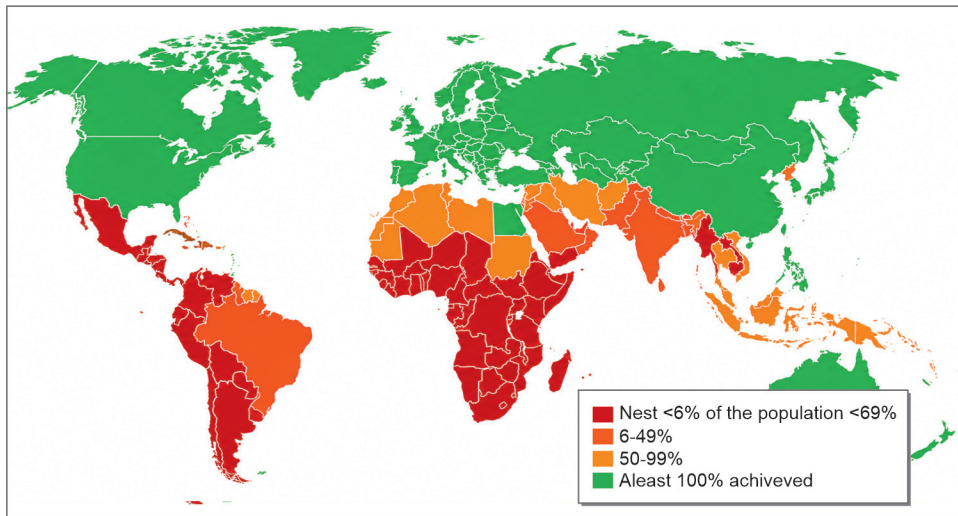


Fig. 8: A Global Map Illustrating Disparities in Surgical Access, Adapted from the Global Surgery 2030 Report. Color-Coded Regions Depict Varying Degrees of Unmet Need, Enabling Rapid Visual Identification of Areas Where Gaps Are Most Pronounced

When designed responsibly, visualizations serve as ethical instruments for advancing health equity and social change.

Moral Geographies and Maps

Maps do more than convey information; they also evoke ethical reflection. When a district is shaded deep red to represent high neonatal mortality, it signifies more than a statistical anomaly. It may

reflect systemic neglect, geographic inequality, and disparities in access to healthcare, nutrition, sanitation, and other essential services.

The ethical dimension of spatial visualization is introduced in **Fig. 9**, which demonstrates how maps can communicate broader social and structural realities beyond epidemiological patterns alone.

Moon (2010) conceptualized these spatial representations as “moral geographies,” visual

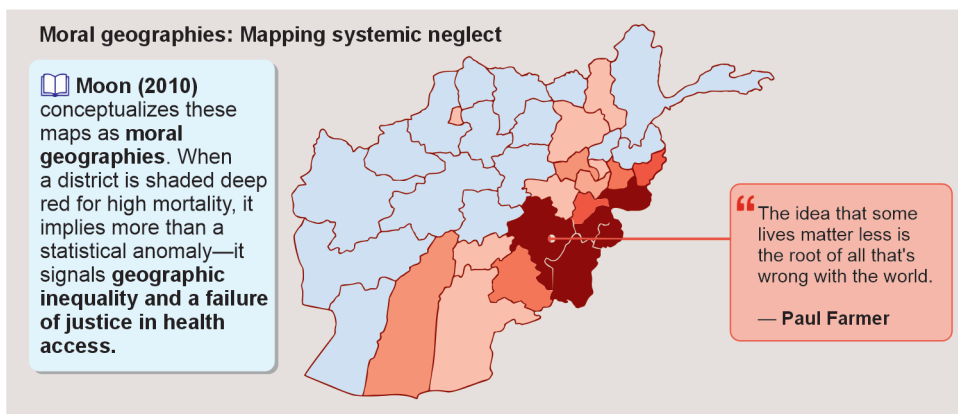


Fig. 9: Moral Geographies in Public Health—Illustrating How Spatial Data Can Represent more than Epidemiological Variation. Districts Shaded in Deeper Tones Indicate Greater Health Burden, Reflecting Underlying Structural Inequities in Healthcare Access, Socioeconomic Conditions, and Policy Attention. Such maps function as “moral geographies” (Moon, 2010), transforming statistical data into visual narratives of justice, inequality, and public health responsibility

landscapes that not only inform but also provoke critical questions regarding fairness, responsibility, and structural inequity. Public health maps, when thoughtfully designed, therefore become instruments of advocacy as well as analysis.

A broader conceptual representation of these ideas is presented in **Fig. 10**, which illustrates how spatial visualization can reveal underlying social and structural inequalities.

This conceptual choropleth-style map demonstrates how spatial visualization can expose geographic inequities in health outcomes and social determinants of health. Areas shaded in deeper red represent greater health burdens (e.g., neonatal mortality), while overlays indicate socioeconomic disadvantage and systemic neglect. The figure highlights the role of maps as both analytical and ethical tools that support evidence-based public health action.

A practical example is provided in **Fig. 11**, which depicts spatial variations in neonatal mortality alongside indicators of socioeconomic inequality.

Such visualizations highlight disparities in life-saving resources, including maternal healthcare, access to clean water, sanitation infrastructure, and nutrition services that often remain obscured in tabular datasets. They reinforce the value of spatial approaches for understanding and addressing health inequities (Krieger, 2006).

A widely cited example is the mapping of lead contamination in Flint, Michigan (2014–2016). Community advocates, researchers, and data journalists visualized the spatial concentration of lead-contaminated water supplies, demonstrating that the crisis disproportionately affected marginalized Black communities. These maps played a pivotal role in raising national awareness, supporting legal action, and informing policy interventions, thereby serving as compelling evidence of environmental injustice and public health neglect.

As Paul Farmer (2003) observed, *“the idea that some lives matter less is the root of all that is wrong with the world”*. Moral geographies make visible where such inequalities persist across space and help translate abstract disparities into tangible evidence for action.

However, the persuasive power of visualization also carries ethical responsibility. Poorly designed maps, such as those employing misleading scales, inappropriate classifications, or stigmatizing color schemes, can oversimplify complex realities and reinforce harmful stereotypes about vulnerable populations. Ethical visualization, therefore, requires not only technical accuracy and clarity but also social sensitivity, transparency, and contextual awareness.

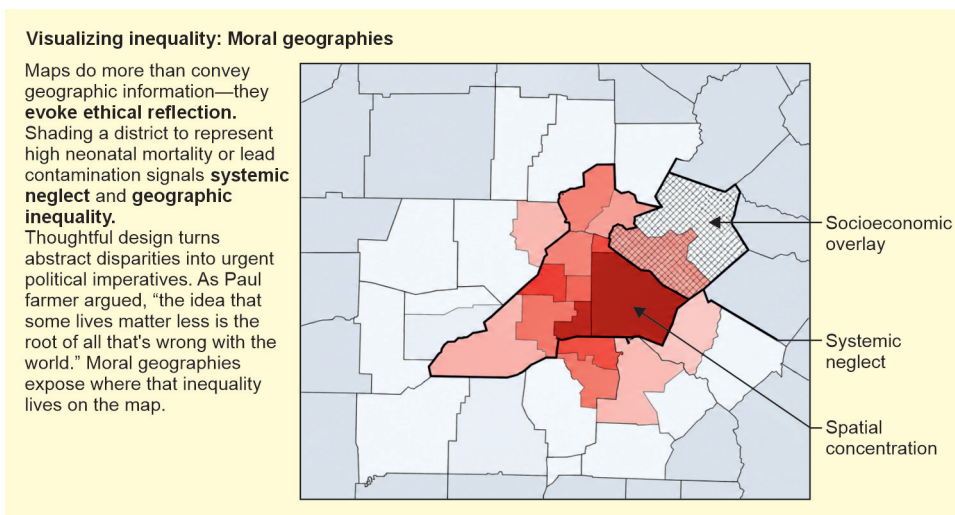


Fig. 10: Visualizing Inequality through Moral Geographies in Public Health

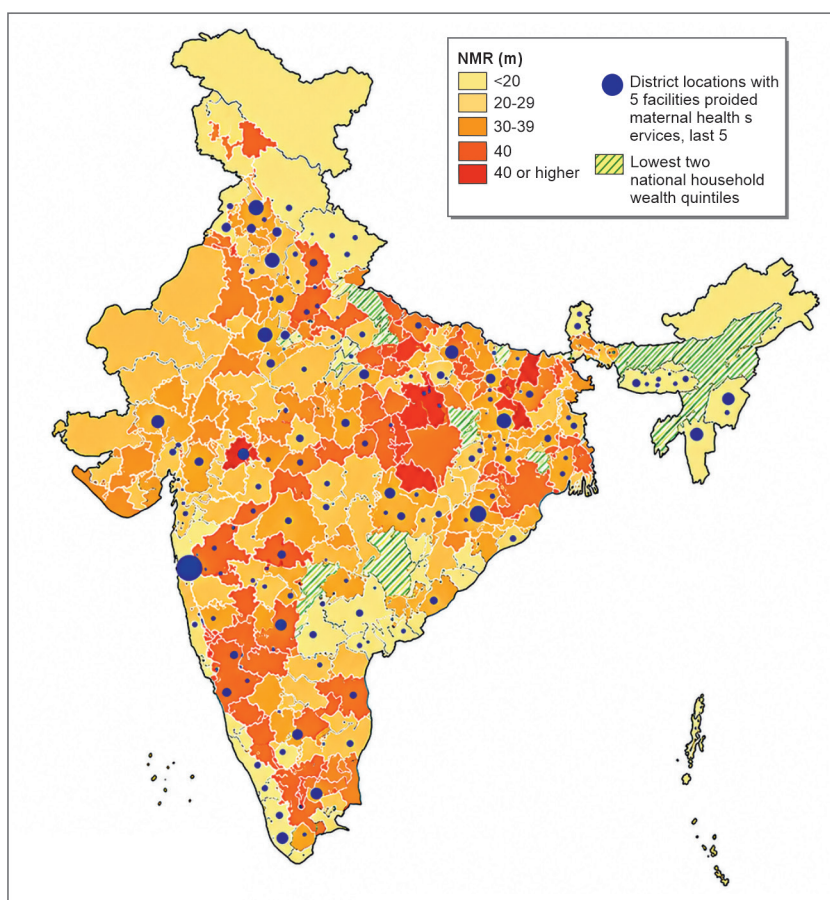


Fig. 11: Choropleth Map of Neonatal Mortality Across Indian Districts with Overlaid Indicators of Socioeconomic Inequality

Ethical Integrity and Visual Responsibility in Health Data Representation

As Mark Monmonier (1996) famously cautioned, “*maps lie*” and so can charts if they are not designed and interpreted with care, transparency, and ethical intent.

In public health communication, visualizations possess immense persuasive power. However, without integrity and transparency, they may distort rather than illuminate. Common pitfalls include truncated axes that exaggerate differences between variables or trends; inappropriate use of color, such as employing red to represent neutral categories, which may unintentionally imply risk or urgency; and selective timeframes that conceal

important trends or create misleading impressions of cause and effect.

For example, a line graph depicting COVID-19 vaccine hesitancy that excludes early fluctuations or omits post-policy changes may create a false impression of either stagnation or progress. Such practices can influence public perception and policy decisions in ways that are inconsistent with the underlying evidence.

As Alberto Cairo (2016) argues in *The Truthful Art*, data visualizations should adhere to the same standards of accuracy, transparency, and honesty expected of statistical analyses. The visual form should enhance understanding rather than manipulate perception.

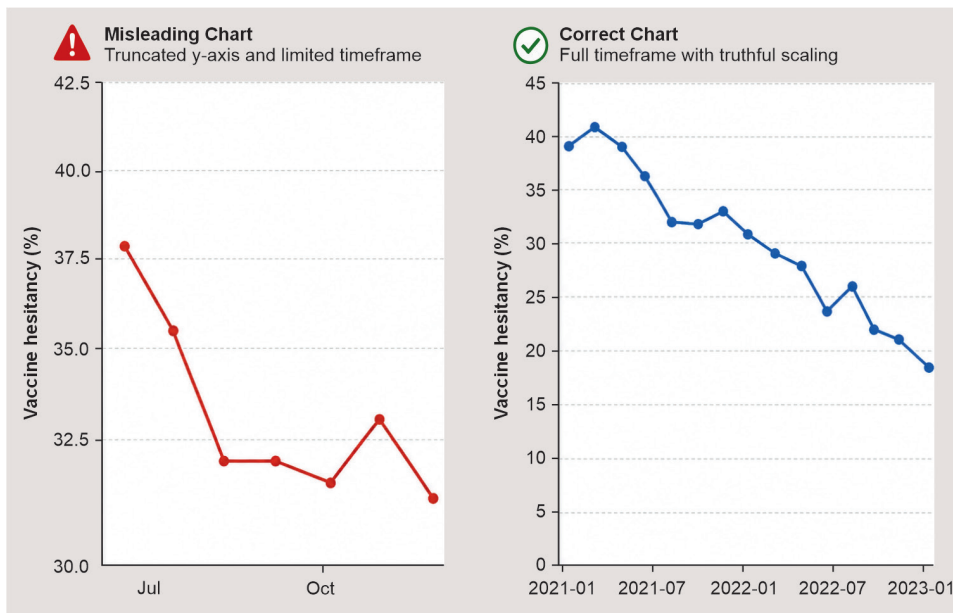


Fig. 12: Comparative Panel Illustrating a Misleading Line Chart (e.g., Using a Truncated Y-Axis and Limited Timeframe) Alongside a Corrected Version That Presents Complete Context and Accurate Scaling

The contrast between misleading and ethically responsible visualization practices is illustrated in **Fig. 12**, which compares a distorted presentation with a corrected version that provides appropriate context and scaling.

To promote ethical and effective communication, health visualizations should adhere to a set of fundamental principles:

ETHICAL CHECKLIST FOR HEALTH VISUALIZATIONS

- Clearly labeled axes with appropriate units and scales.
- Defined timeframes and data collection periods.
- Transparent reporting of data sources and version history.
- Clear legends, annotations, and explanatory notes.
- Appropriate visual encodings that accurately represent underlying data.
- Accessibility considerations, including color-blind-friendly palettes and readable typography.
- Disclosure of methodological limitations where relevant.

Ultimately, visual integrity is not optional; it is foundational to maintaining public trust in health communication. Ethical visualization requires a commitment to accuracy, transparency, inclusiveness, and responsible storytelling, ensuring that graphics inform rather than mislead.

CONCLUSION

In contemporary health systems, data visualization is not merely an enhancement; it is a strategic imperative for evidence-informed decision-making. From global pandemic dashboards to nutrition surveillance systems and geographic health intelligence platforms, visual tools have demonstrated their capacity to clarify multi-dimensional complexity and drive health action through accessible, evidence-based, and ethically grounded storytelling. However, with this power comes responsibility. Inaccurate, ambiguous, or aesthetically manipulative graphics risk misrepresenting populations, obscuring inequities, and misleading stakeholders. As global health becomes increasingly data-intensive, visualizations must function not only as analytical tools but

also as instruments of advocacy, accountability, and public engagement, faithfully representing the people and communities behind the data (Wilkinson, 2005). The concepts introduced in this chapter provide the foundation for understanding how visualization transforms complex health information into meaningful insight. In the next chapter, we examine how the characteristics of health data, whether quantitative or qualitative, spatial or temporal, influence visualization choices, analytical approaches, and interpretive objectives.

Disclosure: The author used AI-assisted tools to help prepare selected images included in this manuscript solely for educational purposes. The author assumes full responsibility for all content presented in the manuscript.

SUGGESTED READING

1. Bostock, M., Ogievetsky, V., & Heer, J. (2011). D³: Data-driven documents. *IEEE Transactions on Visualization and Computer Graphics*, 17(12), 2301–2309.
2. Cairo, A. (2016). *The truthful art: Data, charts, and maps for communication*. New Riders.
3. Dong, E., Du, H., & Gardner, L. (2020). An interactive web-based dashboard to track COVID-19 in real time. *The Lancet Infectious Diseases*, 20(5), 533–534.
4. Farmer, P. (2003). *Pathologies of power: Health, human rights, and the new war on the poor*. University of California Press.
5. Few, S. (2009). *Now you see it: Simple visualization techniques for quantitative analysis*. Analytics Press. Heer J, Bostock M, Ogievetsky V. A tour through the visualization zoo. *Commun ACM*. 2010;53(6):59–67.
6. Hripcsak G, Duke JD, Shah NH, Reich CG, Huser V, Schuemie MJ, et al. Observational Health Data Sciences and Informatics (OHDSI): opportunities for observational researchers. *Stud Health Technol Inform*. 2015;216:574–8.
7. Kosslyn SM. *Graph design for the eye and mind*. New York (NY): Oxford University Press; 2006.
8. Krieger N. A century of census tracts: health and the politics of mapping in the United States, 1910–2010. *Am J Public Health*. 2006;96(2):197–205.
9. Mayer RE, editor. *The Cambridge handbook of multimedia learning*. New York (NY): Cambridge University Press; 2005.
10. Meara JG, Leather AJM, Hagander L, Alkire BC, Alonso N, Ameh EA, et al. Global Surgery 2030: evidence and solutions for achieving health, welfare, and economic development. *Lancet*. 2015;386(9993):569–624.
11. Monmonier M. *How to lie with maps*. 2nd ed. Chicago (IL): University of Chicago Press; 1996.
12. Moon G. Health geography: progress, challenges and prospects. *Health Place*. 2010;16(3):516–9.
13. Raghupathi W, Raghupathi V. Big data analytics in healthcare: promise and potential. *Health Inf Sci Syst*. 2014;2:3.
14. Rogers, D. (2019). Big data in health: Opportunities and challenges. *Health Informatics Journal*, 25(3), 875–883. <https://doi.org/10.1177/1460458218775545>
15. Tufte ER. *The visual display of quantitative information*. Cheshire (CT): Graphics Press; 1983.
16. Ware C. *Information visualization: perception for design*. 4th ed. Cambridge (MA): Morgan Kaufmann; 2020.
17. Wilkinson L. *The grammar of graphics*. 2nd ed. New York (NY): Springer; 2005.