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A checklist for designing and improving the visualization of scientific data

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Creating clear and engaging scientific figures is crucial to communicate complex data. In this Comment, I condense principles from design, visual perception and data visualization research in a checklist that can help researchers to improve their data visualization, by focusing on clarity, accessibility and design best practices.

The visualization of data accelerates comprehension by revealing trends and patterns. Figures have always been fundamental in the natural sciences, translating complex data into visual insights. Early scientific illustrations documented specimens and concepts, while modern data visualization evolved through pioneers such as William Playfair, who introduced graphical methods for numerical data[1]. Biomedical scientists, including John Snow and Florence Nightingale, expanded this approach to reveal patterns in public health.

Foundational works in information design offer general guidance[2], but visualizing biological data requires additional considerations. Modern biological research relies on a wide range of visualizations – from tables and charts to images, maps and phylogenetic trees – to effectively convey insights from the molecular to the organismal scale. Each visualization type has its own conventions and challenges, yet biologists often receive little to no formal training in data visualization.

There is some help available for specific applications, such as conference posters[3–5], graphical abstracts[6], or microscopy images[7–9]. A series of articles highlights different aspects of scientific data visualizations[10]. Books also address biological data visualization, from visualizations of cellular measurements to the coding of data visualizations[11,12]. But despite these resources, designing effective figures remains challenging, as data sets have become increasingly complex. In this Comment, I explain how to apply data visualization principles[13] to improve or design figures in the life sciences, and include a checklist (intended as a flexible guide, rather than a set of strict rules). It can be applied at any stage of figure design, whether starting from scratch or needing to refine an existing chart. Before using the checklist (Supplementary Material 1), defining a clear key message and considering the target audience's expectations is essential. Finally, I provide additional resources and tools to support further skill development.

Basic considerations

Choose a chart. For numerical data, choose a chart that accurately represents your data and, crucially, is understandable to your audience. The choice of chart type also depends on the data type, whether this involves categories, distributions, time series, or proportions. Common charts – such as bar, line and pie charts – are widely understood, while specialized charts (such as boxplots or Kaplan–Meier plots) may require domain-specific knowledge. Consider your audience's familiarity, and follow best practices for clarity.

Research in computational sciences continues to explore how humans interpret charts. Studies show that people excel at reading charts with a common scale, such as bar charts (*x* axis) and scatter plots (*x* and *y* axes), whereas interpreting charts without a shared axis, such as line and pie charts, is more challenging. Studies also highlight concerns with commonly used charts, and, for example, advocate against bar charts for statistical distributions, as they obscure data variability[14].

Simplify charts. Even with a suitable chart type, your visualization may still be difficult to understand. If you chose a basic chart but the message is complex, focus the audience's attention by improving annotations, labels, and layout, or by reducing the data shown to emphasize the key message. Splitting data into two or multiple charts can help separate insights, and zoomed views can highlight both overall trends and details. For complex datasets, 'small multiples' – a series of identical charts sharing the same axis layout – can simplify interpretation by showing one grouping factor at a time (for example, gene expression in different tissues) (Fig. 1a). Tools including Python and R offer features, such as 'gridding' or 'faceting', to create these visualizations efficiently. Gradual presentation of complex charts, using animated slides or successive charts that highlight different data subsets, can also improve clarity (Fig. 1b). For specialized or uncommon chart types, which are at times necessary for scientific data, provide clear guidance (titles, subtitles, legends, annotations) that helps the audience. Descriptive titles, direct labels or arrows can further highlight key points and improve understanding.

Text in charts. Text is crucial in figures. Text should explain all units, axes, tick marks, colours and key data points, while titles and legends provide essential context – but be careful to avoid redundancy and superfluous text (for example, when providing units in titles, axis labels, and tick marks). Text must be legible in both font choice and size, and should align with the audience's vocabulary – ambiguous abbreviations are a common pitfall. Testing labels and titles with colleagues outside your field can help to identify unclear elements (Fig. 1c). Font size should remain readable when resized, and non-horizontal text should be avoided where possible. Rotating charts can help create space for labels in categorical data, but may not suit line charts. Most modern fonts used in a scientific context are legible, but mixing fonts or styles for emphasis (common in graphic design) should be used cautiously in scientific figures, as it can confuse (for instance, italics often indicates gene names). Familiar keywords and jargon-free titles are considered to correlate with higher citations.

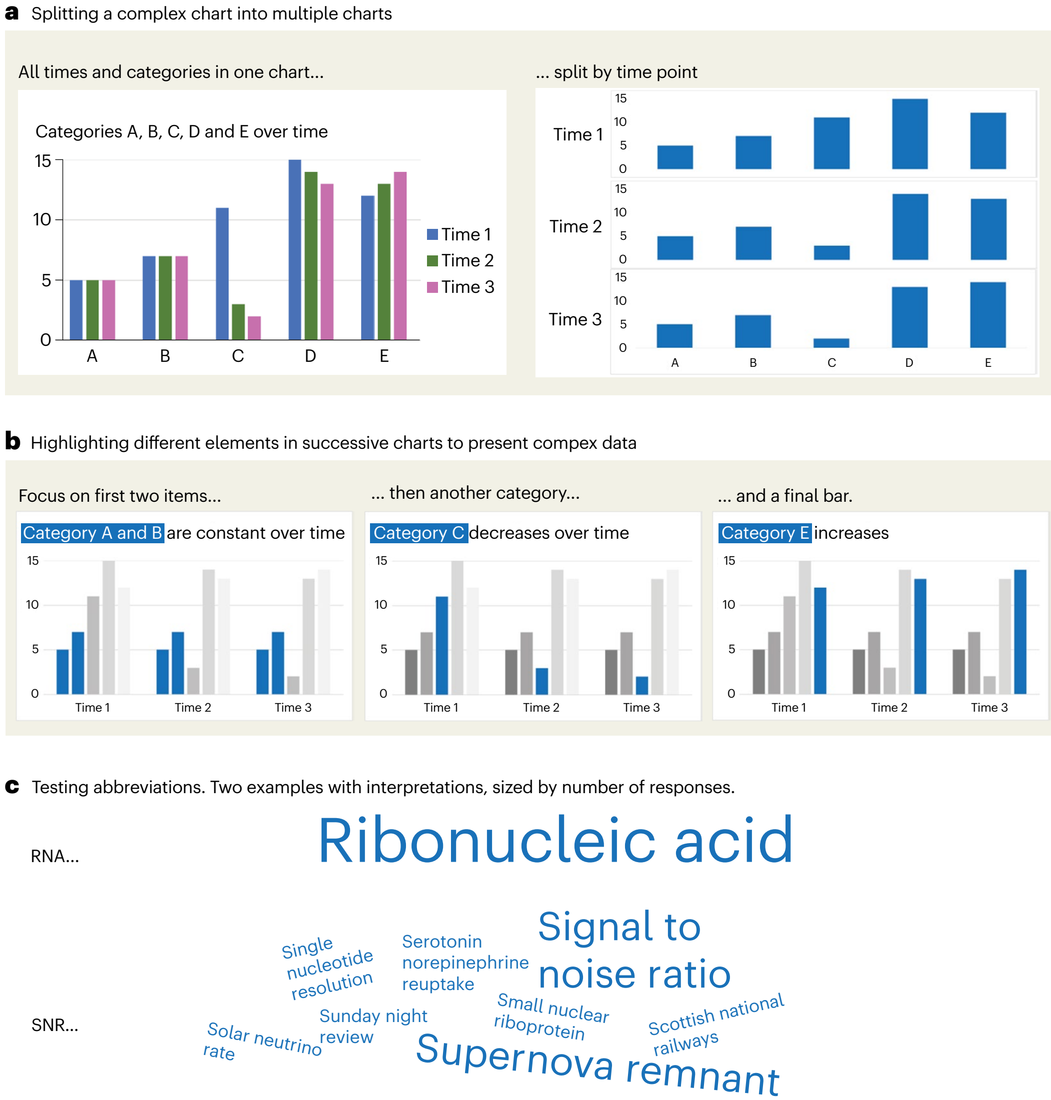

Fig. 1 | Basics for figures. a, Breaking up complex charts into several charts with a shared axis layout as small multiples is a possibility for simplifying complex messages. Note that this usually does not require more space. **b**, Presenting successive charts that each highlight a different aspect is another strategy for simplifying complex messages. Note that this works in presentations but may be limited in publications because of space restrictions. **c**, A strategy for querying the meaning of abbreviations before using them in charts. Note that even if legends and/or the text provide explanations, any uninterpretable abbreviation reduces comprehension.

Design

Layout. Effective layout is key to creating clear and accessible figures. Although multipanel figures and posters require clear reading directions, grid organization and sufficient white space for easy navigation, thoughtful layout within a single chart is equally important for improving legibility. In both cases, align meticulously: use grids for multipanel figures, and carefully position titles and labels in single charts. Position text strategically: titles are best placed at the top left, while data sources fit well at the bottom. Avoid text rotation, as non-horizontal text slows reading speed (and frustrates audiences). Keep labels and text horizontal whenever possible, for example by rotating charts, or flipping *x*- and *y*-axes (the exception is line charts). Directly labelling data points instead of relying on legends can improve clarity. For the chart itself, you will have to choose which data to map to which axis, or the length of the axes (for instance, an elongated *x*- or *y*-axis).

Colour schemes. Colour serves multiple purposes in scientific figures. It can show the natural appearance (in photos of specimens, or national colour codes, for instance), enhance understanding by contrasting or highlighting key elements, encode quantitative information, or add visual appeal to make figures more memorable.

Regardless of its purpose, colour choices should prioritize accessibility and consistency. First, ensure that colours provide sufficient contrast with the background, especially for small chart elements.

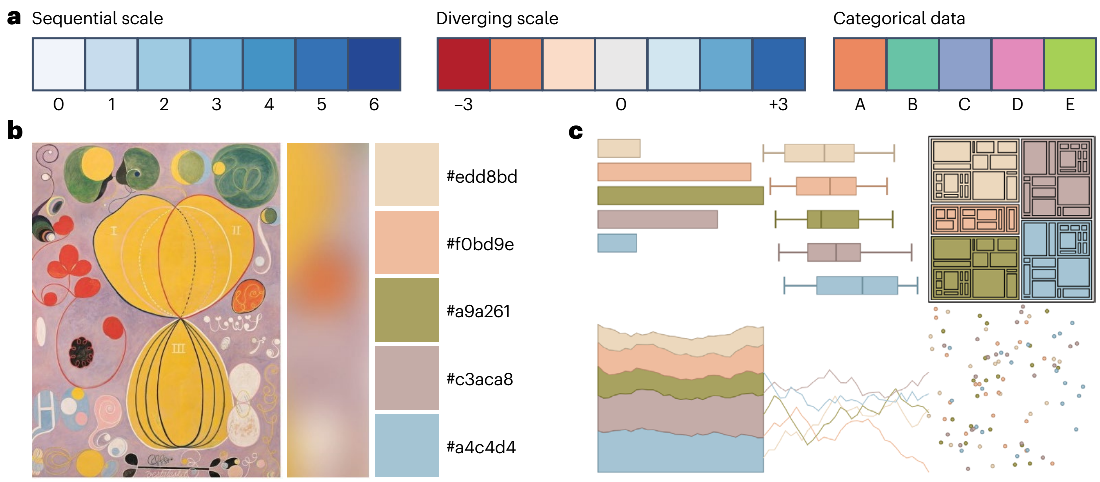

Fig. 2 | Designing figures. **a**, Example colour palettes for encoding numerical data in charts. Note that most colour palettes for more than four categories are not colour-blind-safe. **b**, Colours for categorical data or for decorative elements (for instance, in posters) can be extracted as RGB or HEX codes from a favourite piece of art (or similar). Note that the resulting colour schemes may not be acceptable by publishers that provide in-house colour palettes. The image shown here is by Hilma af Klint, public domain, via Wikimedia Commons. **c**, Before use, extracted colours can be applied to test data in various chart types with the tool VizPalette; for the example colour palette shown, this reveals that light colours may work for charts with large areas, but are too faint when applied to the visualization of thin lines or data points in scatter plots.

Second, maintain consistent colours (a 'colour scheme') across figures to improve clarity. To maximize accessibility, select colours that are visible to colour-blind and visually impaired audiences. Note that colour perception also varies among visually able audiences. A good test is whether figures are still understandable in greyscale.

Generally, colour should be avoided as the sole channel for key information, and fully explained, in legends for instance. Using labels or symbols alongside colour can reinforce key points without overwhelming the reader. Finally, use colour sparingly to draw attention to important data, rather than applying it broadly.

When designing a colour scheme, tools such as Paletton (https://paletton.com/) can help to select harmonious colour combinations. Next, however, test the accessibility of colours: most computers have settings to simulate colour blindness and greyscale, and more advanced analyses can be done with web-based tools (such as the WebAIM contrast checker).

Encode data with colour. Colour is essential for contrasting categories, encoding quantities, trends and groups. In scatter and dimension-reduction plots – for example, from principal component analyses – groups are distinguished by colour; in line charts, ordinal groups can be shown with progressively darker shades; and in heatmaps, red/blue scales can highlight values above or below a reference point. Colour choice depends on data type (Fig. 2a). For categorical data, without inherent order, use distinct colours (or patterns in greyscale). For sequential data (such as gene-expression values), apply a single hue with varying saturation (for instance, light to dark blue). If a multihue scale is necessary to better differentiate data ranges, use palettes that are designed for sequential data (for instance, iridis, not rainbow, colours). For diverging data (for instance, above/below 0 °C, medians, or reference values) use two contrasting hues with a neutral centre (for example, white or grey) to highlight deviations. Use colour only when necessary, and always include a legend to explain its meaning (see Table 1 for colour tools).

On beauty. Once charts and figures are functional and effective, you can also consider making them beautiful. Although beauty is subjective, research shows that engaging visual elements can improve attention and recall. Positive emotions triggered by appealing charts may boost user engagement, while data animations designed to evoke joy or curiosity can further capture interest. Beauty can be achieved by different means: attractive colour schemes (Fig. 2b, c), symmetrical layouts (for instance, no gaps in multipanel figures; enough white space to clearly separate elements), and attractive, legible charts and text sized proportionally[12] in the final figure. Another possibility is to include eye-catching visuals, such as icons or pictograms, to complement text, which enhance memorability (Table 1). Note that journals may restrict icons in figures for explaining a workflow or where necessary for differentiation; however, in posters and slides, they may also be included to make axes more self-explanatory.

Feedback

The one-second test. A quick way to evaluate figure effectiveness is the one-second test. Ask a colleague, ideally one not familiar with the data, to glance at the figure and describe where their eyes go first (without interpreting the data). Ask: "What do you see first?". This helps to identify which elements have the most 'visual weight' or 'salience'. The most prominent element should be the key message or main data, as human visual perception is fast, but very limited to a few elements at a time. Distracting elements, such as bright colours, cluttered legends, or oversized labels, may unintentionally draw attention away from the data. Perform this test with early draft versions to identify what aspects need improvement.

Reverse feedback. To provide 'reverse feedback', a colleague unfamiliar with the data attempts to interpret your figure without guidance. Ask: "Explain to me what you see". Observing their thought process reveals which elements are confusing or unclear

Table 1 | Resources for making figures

Name	What for?	Website
Chart types		
DataViz Catalogue	A collection by Severino Ribecca of chart types and their applications	http://www.datavizcatalogue.com/
Python Graph Gallery	The Python Graph gallery, by Yan Holtz, with code and application examples	https://python-graph-gallery.com/
Molecular Cytology Shiny Apps	Web applications for generating uncommon charts (such as beeswarm plots, volcano plots, or superplots), by Joachim Goedhart	https://huygens.science.uva.nl/
Colour		
Color Brewer	Colour schemes developed for thematic maps; can be applied when encoding numerical data in life-science figures, by Cynthia Brewer	https://colorbrewer2.org
Coblis	Colour-blindness simulator and information about colour blindness	https://www.color-blindness.com/coblis-color-blindness-simulator/
Webaim	Colour-contrast checker	https://webaim.org/resources/contrastchecker/
VizPalette	Test colour schemes with example data in various chart types, by Susie Lu and Elijah Meeks	https://projects.susielu.com/viz-palette
Icolorpalette	Extract colours from images	https://icolorpalette.com/color-palette-from-images
Icons		
General	Creative Commons 0 (CC0) icons for general terms	https://www.svgrepo.com/
BioIcons	Icons for molecular biology, from various sources; site by Simon Dürr	https://bioicons.com/
Phylopic	More than 9,000 icons of plants and animals, collected by Mike Keesey	http://phylopic.org/
SciDraw	Icons of model organisms and lab equipment. Collection supported by Sainsbury Wellcome Centre	https://scidraw.io/
BioArt	National Institutes of Health collection of more than 2,000 icons	https://bioart.niaid.nih.gov/

(Fig. 3). Refrain from offering explanations; instead, ask specifically about the different figure elements, such as chart selection, text choices, layout, and colour interpretation. Reverse feedback is a method in computer interface design to understand usability during prototyping.

Focus the attention. To emphasize key points, consider muting or removing less important elements (see Fig. 3 for an example workflow). Reducing point size, using grey for non-critical content or text (note that not all publishers allow, for instance, grey axes in charts), or adjusting transparency (as in crowded scatter plots) can help to minimize visual distractions. Also, removing unnecessary boxes, bold axes, or excess tick marks can improve clarity. Gridlines should be limited to major units and kept thin to avoid visual clutter; note that unusual axis layouts such as log scales may require gridlines. Replace redundant axis labels with concise text or annotations to simplify the figure; note that in scientific charts, axis labelling is essential, but be mindful of excessive text. Where possible, use direct data labels instead of extensive legends to reduce complexity.

Background and excessive colours should be avoided unless essential; if used, ensure that they provide strong contrast with data points. By combining thoughtful colour choices, clear layout, and selective emphasis on key data points, you can effectively guide the viewer's focus and improve the figure's overall impact. Focusing on salient elements in figures, as Tufte suggests, aligns with how the brain processes visual data[2]. Beyond removing or muting, visual attention can also be focused by improving the layout by aligning elements (all tick marks, text, titles, legend elements, panel labels), filling empty spaces in multipanel figures, and ensuring symmetry – for instance by changing the size of individual panel elements.

Tools

A comprehensive review of many common software packages used for illustrations, as well as their advantages, disadvantages and pricing, is available elsewhere[15]. For free vector graphics, Inkscape offers a practical option with growing features, such as icon import and data processing via scripts. Adobe Illustrator is a widely used commercial alternative, but high-resolution figures can also be generated with PowerPoint.

Conclusion

This guide outlines a practical approach for biologists to design clear and effective scientific figures. Any figure-design process is, however, iterative, often requiring adjustments and refinements to improve clarity, highlight key insights, or better suit the data and audience – and at times this means going back to the beginning of the checklist. In addition, all points raised in these guidelines work in conjunction with each other, meaning that we may deliberately omit items from the checklist, to ensure that our figure meets other, pre-existing design choices (for instance, in maps, north is shown at the top; in palaeobiology timelines, the x-axis points to the left; in epigenetics, HiC plots are flipped by 90° and shown as triangles). As biological data continue to grow in complexity and scale, mastering visualization techniques is increasingly important. The recommendations provided here offer

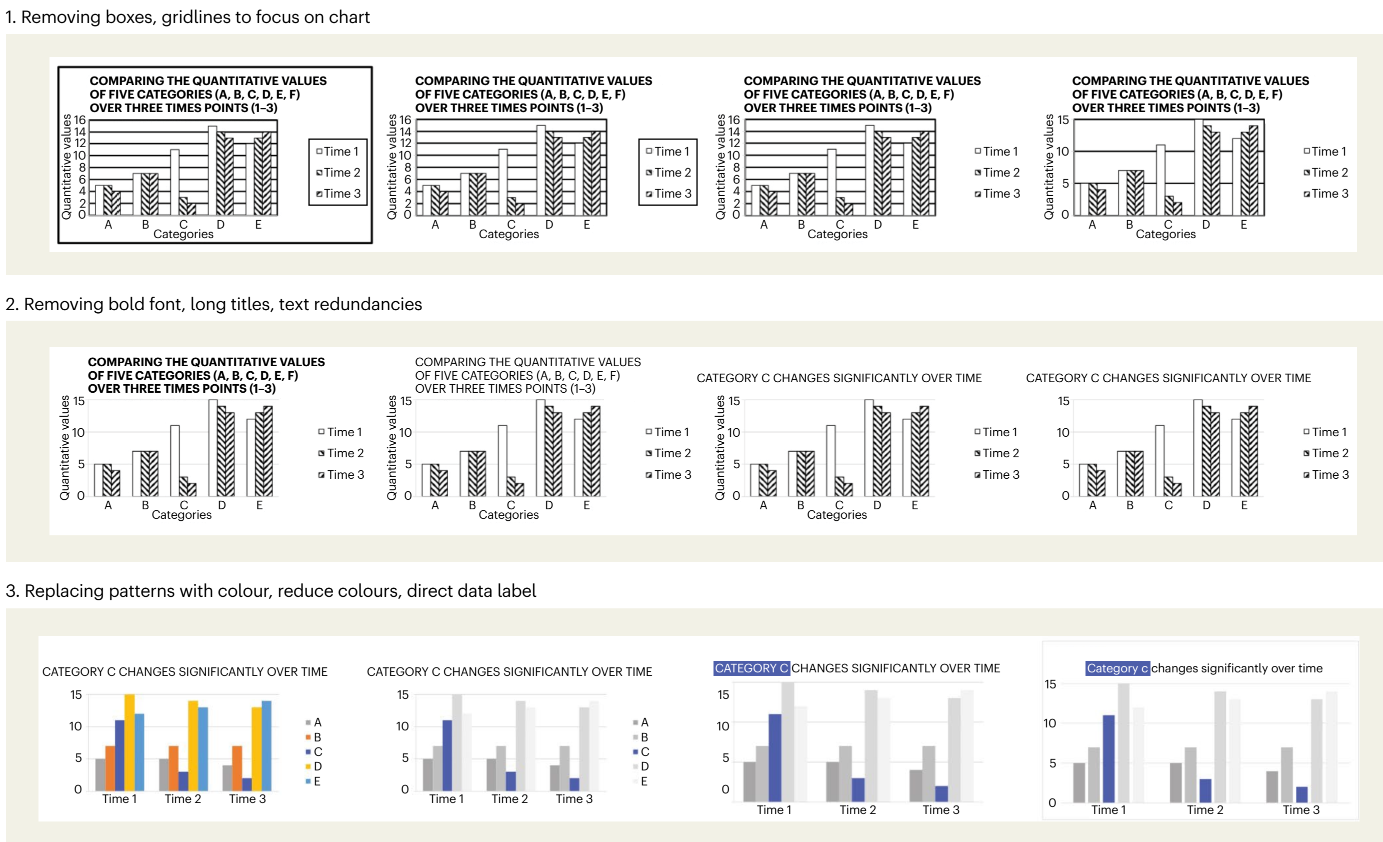

Fig. 3 | Feedback for figures. Stages of an example workflow for figure improvements: removing unnecessary elements that draw attention, then attending to font, annotations, and titles, and finally working on colours and colour legends.

a starting point for biologists aiming to communicate their findings more effectively.

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