

## REVIEW ARTICLE

# Artificial intelligence-assisted scientific figure design in international publishing and its implications for editorial responsibility

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## Abstract

Reviewers, editors, and readers judge a manuscript partly through its figures, which carry evidential as well as rhetorical weight. This review treats figure production as a design problem and as a question of publication equity. Where communicative polish influences how otherwise comparable work is assessed, uneven access to professional illustration, specialized software, mentoring, and visual-literacy support becomes a justice-relevant disadvantage. Kept under human control, artificial intelligence (AI)-assisted tools may narrow part of that gap by helping with figure planning, layout, captioning, accessibility checks, and reproducible plotting. Generative systems also carry their own hazards: fabricated elements, semantic drift, bias, exposure of confidential information, and broken provenance. We propose a five-stage, theory-informed framework in which authors define the scientific claim, choose the visual grammar, draft with bounded AI support, validate every visible element against source material, and prepare files with provenance and disclosure. A worked application to a protein X-ray crystallography workflow shows how the framework can be implemented in a technically demanding setting; the application is explicitly non-empirical. Throughout, AI serves as a drafting and checking aid, not as a source of evidence, and accountability stays with the author.

**Keywords:** Scientific figure design; Artificial intelligence; Visual communication; International publishing; Accessibility; Image integrity; Editorial responsibility; Research equity

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**Citation:** Ahiri A. Artificial intelligence-assisted scientific figure design in international publishing and its implications for editorial responsibility. *Design+*. doi: 10.36922/DP026250026

**Received:** June 17, 2026

**Revised:** August 13, 2026

**Accepted:** August 17, 2026

**Published online:** September 3, 2026

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## 1. Introduction

Manuscripts are not evaluated through text alone. Reviewers often move between the abstract, the main figures, and the captions before they read the methods in detail. Figures are a second argumentative channel: they condense evidence, display relations, and help a reader judge whether a study is coherent enough to examine closely. Practical guidance has long stressed audience, message, layout, medium, and caption clarity<sup>1,2</sup>, but such recommendations do not explain why particular design choices succeed or fail. **Figure 1** situates scientific figures within the editorial pathway from research question to decision.

The theoretical basis matters because figures are read through perceptual and cognitive systems. Classic work on graphical perception shows that people compare

position and length more accurately than area, angle, or color intensity.<sup>3</sup> Later online experiments confirmed that controlled perceptual testing can evaluate visualization design choices at scale.<sup>4</sup> What follows from this is that a design choice is really a decision about which perceptual task the reader will be asked to perform.

A scientific figure also has a visual grammar. Marks, spatial arrangements, panels, arrows, labels, scales, and legends form a system, and that system has to match the claim. Early work on automatic graphical presentation argued that visual forms can be selected according to data relations and tasks.<sup>5</sup> More recent synthesis shows that effective visual data communication depends on aligning the visual form with the reader task, the data structure, and the interpretation expected from the figure.<sup>6</sup>

Color illustrates the problem well. A palette may look attractive while still distorting magnitude, creating false categories, or excluding readers with color vision differences. Crameri *et al.*<sup>7</sup> argue that color choices can alter scientific interpretation and should be considered part of the method rather than a cosmetic preference. In international publishing, the consequence is practical: a misleading color scale can slow review, invite correction, or weaken trust in the study.

Attention and grouping matter just as much, since readers do not inspect every element with equal effort. Feature integration and guided search research show that visual attention depends on simple features and on top-down expectations.<sup>8,9</sup> Perceptual organization research adds that connectedness and grouping affect what viewers perceive as a unit.<sup>10</sup> These principles bear directly on multipanel figures, workflows, and graphical abstracts, where spacing, borders, arrows, and label placement guide the reading path.

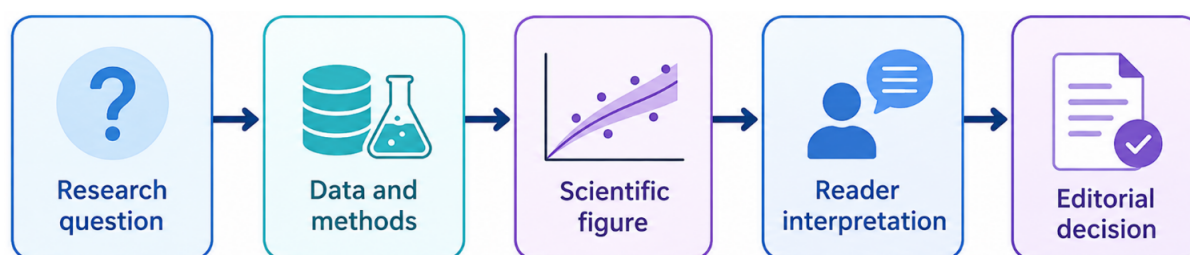
Artificial intelligence (AI) changes the production process without transferring the author's responsibility to the tool. AI systems can propose layouts, check captions,

translate a method into a workflow outline, or generate plotting code, and these functions may save time and lower technical barriers for authors who have no professional design support. The same systems can invent labels, suppress uncertainty, or make schematic content resemble observed evidence. The framework proposed here therefore treats AI as bounded assistance and puts human validation at the center of figure production. Recent practical tutorials and checklists likewise emphasize message definition, legibility, and context-sensitive figure design.<sup>11-13</sup>

### 1.1. Justice, resource asymmetry, and the central argument

The central normative claim of this review is that figure design becomes a matter of justice when access to the resources required for effective visual communication is unevenly distributed. Figures are part of how evidence becomes visible and reviewable. If reviewers can more easily understand and trust work presented with professional visual expertise, then unequal access to that expertise may affect the conditions under which scientific contributions are heard and evaluated. The inequality at stake is not aesthetic: it concerns access to software, specialist illustration, mentoring, time, and tacit knowledge about international editorial conventions.

The claim needs to be stated carefully. Not every difference in presentation quality is an injustice, and the literature has not quantified disparities in figure-design support as extensively as it has quantified other communication burdens. Research on international scientific communication, however, shows that researchers working outside dominant linguistic and resource contexts can incur additional time, financial, and participation costs.<sup>14</sup> From the perspectives of distributive justice and epistemic justice, a disparity becomes normatively important when resources only indirectly related to scientific merit systematically shape whose evidence is easiest to inspect, whose arguments are easiest to follow, and whose work appears publication-ready.<sup>15</sup>



**Figure 1.** Editorial role of scientific figures in international publishing. The figure shows how visual representation connects the research question, data and methods, reader interpretation, and editorial decision.

Under this framing, AI supports justice when it lowers the cost of basic design assistance without weakening standards of evidence. Its value lies not in making figures more attractive but in giving structured drafting and feedback to researchers who would otherwise go without. The potential is conditional. Paid access, uneven digital infrastructure, model bias, limited language coverage, and unequal AI literacy can all reproduce or deepen existing inequalities. What is being sought, then, is access with accountability, and not a technological substitute for institutional investment in training and support.

## 1.2. Review approach and literature selection

This article is a theory-informed, structured narrative review, not a systematic review or meta-analysis. The literature was organized around five domains: (i) graphical perception and visualization design; (ii) attention, cognitive load, diagrammatic reasoning, and visual rhetoric; (iii) visualization literacy and accessibility; (iv) reproducibility, image integrity, and scientific publishing ethics; and (v) AI-assisted scholarly communication, editorial policy, and publication equity. Foundational studies were retained regardless of publication year, since several remain the basis of contemporary visualization theory.

For the focused revision and update, searches and source checks were conducted through August 3, 2026. PubMed was used for biomedical and scientific-publishing literature; ACM Digital Library and IEEE Xplore were consulted for visualization and human-computer interaction research; and the official websites of the International Committee of Medical Journal Editors (ICMJE), World Association of Medical Editors (WAME), AccScience Publishing, Elsevier, and Springer Nature were consulted for current editorial guidance. Search concepts combined scientific figure design, data visualization, graphical perception, image integrity, generative AI, AI-assisted writing, publication ethics, editorial policy, accessibility, and research equity. Material published between 2020 and 2026 was prioritized, with earlier foundational works retained.

Eligible sources were peer-reviewed empirical studies, conceptual or methodological reviews, foundational theoretical papers, and authoritative editorial-policy documents in English. Marketing-only pages, purely aesthetic tutorials without an evidence base, and sources with unclear provenance were excluded. The material was synthesized qualitatively, with each source mapped to a barrier, a design principle, an AI-supported task, an ethical risk, or a validation control. Because the purpose here is conceptual synthesis and framework construction, rather than exhaustive effect estimation, no Preferred Reporting Items for Systematic Reviews and Meta-Analyses

(PRISMA)-style screening flow or pooled quantitative analysis was undertaken.

## 2. Barriers to publication-ready figures

The first barrier is technical. Journals specify file type, resolution, dimensions, font size, line weight, panel labels, and caption placement. A figure that looks clear in a presentation may fail once it is reduced to journal column width: labels become unreadable, strokes disappear, and compressed image panels lose diagnostic detail. Faults of this kind are not merely cosmetic, because they change what the reader is able to inspect.

Technical problems often begin in the workflow. A plot may start in a spreadsheet, move to presentation software, become a screenshot, and end up in a word-processing file. Each step can disconnect the figure from the data and make later revision harder. A figure that cannot be traced back to a data table, a script, or an editable diagram is difficult to audit and risky to revise.

The second barrier is visual literacy. Figures often fail not because the underlying study is weak but because the reader cannot identify the intended comparison, the reading order, the mapping of groups to symbols, or the meaning of color and annotation. Good design reduces the effort needed to evaluate evidence; poor design forces the reader to solve the layout before assessing the science.

The third barrier is unequal access to design support. Some authors work with institutional illustrators, licensed professional software, experienced visualization collaborators, and supervisors who routinely prepare figures for international journals. Others rely on screenshots, improvised templates, free tools, and repeated trial-and-error revision. When presentation quality influences how efficiently evidence can be inspected, that asymmetry ceases to be a matter of convenience and becomes a potential fairness issue in the publication process. AI-assisted design may close part of the gap, but only where it supports accountable decisions and leaves source control and scientific judgment untouched.

A fourth barrier is editorial fit. Journals differ in figure placement, graphical abstract expectations, reuse rules, image manipulation policies, and production requirements. A technically correct figure may still be unsuitable for a target journal if its caption is incomplete, its panels are not cited in order, or its file structure cannot be edited by production staff.

Data complexity is the fifth barrier. Large, multimodal, or highly dimensional outputs can be difficult to compress into a single figure without hiding uncertainty, overloading the reader, or privileging one view of the evidence. AI

can help organize candidate layouts or panel structures. Determining which observations are scientifically important requires authorial and domain expertise and should remain a human judgment.

The sixth barrier concerns research integrity. Inappropriate image manipulation and duplication are documented problems in biomedical publishing.<sup>16,17</sup> Generative tools complicate the picture because they can redraw, upscale, clean, or synthesize visual material in seconds. The difficulty is not that every AI-assisted edit is improper; it is that undocumented or non-reproducible editing severs the link between the visible figure and the underlying evidence.

Two cross-cutting pressures amplify all six barriers. The first is timing, because figures are often assembled late, close to submission. Late production encourages shortcuts: screenshots instead of editable files, copied legends instead of precise captions, quick color changes instead of a coherent visual system. Treating figure planning as part of manuscript planning, rather than as a final formatting task, avoids most of this.

The second pressure is cross-disciplinary reading. International journals frequently assign reviewers from

adjacent fields, so a symbol or workflow that seems obvious to the authors may be unfamiliar to a reviewer. Captions and labels should explain the visual logic and not merely name the panels. A reader should be able to identify what is compared, what is measured, and what remains uncertain without reconstructing the whole manuscript. [Figure 2](#) summarizes the six recurrent barrier categories, with timing pressure and cross-disciplinary reading treated as cross-cutting.

### 3. Visual communication theories for scientific figure design

This review builds on four connected bodies of theory. The first is visual encoding and graphical perception. A figure should encode the intended comparison through an accurate perceptual channel: when the claim concerns relative magnitude, position on a common scale is usually safer than area or angle; and when it concerns categories, color may help but should never be the only code. This is why the framework begins with a one-sentence figure claim, before any layout is drafted.

The second body is attention, grouping, and hierarchy. A figure is read along a guided path. Proximity can imply



**Figure 2.** Main barriers to the production of publication-ready scientific figures. The diagram summarizes six recurrent categories: technical requirements, visual literacy, software access, editorial fit, data complexity, and research integrity. Timing pressure and cross-disciplinary reading are cross-cutting pressures discussed in the text.

relation, alignment can imply sequence, and enclosure can imply membership, but these effects only help when the design uses them deliberately. In a multipanel figure, a badly placed border or legend can lead the reader to infer the wrong comparison. The framework therefore asks for a figure brief that states the reading order, the panel structure, and the meaning of each grouping device.

The third body is cognitive load and multimedia learning. Scientific readers are already holding the research question, the method, the abbreviations, and the statistical assumptions in memory. A figure that splits related information across distant labels, repeated legends, or unexplained arrows adds extraneous load on top of that. Cognitive load theory and multimedia learning research show that instruction is clearer when the design reduces unnecessary mental integration, aligns words with visuals, and uses multiple representations only where each one has a clear function.<sup>18-22</sup>

The fourth body is diagrammatic reasoning. Diagrams are useful because they externalize relations that are hard to hold in memory, and they mislead when they hide assumptions or present a conceptual relation as an observed result. Research on diagrams, animation, visual-spatial displays, and dual coding shows that visual representations help when they match the task and when the reader can map labels onto the underlying concept.<sup>23-27</sup>

Visual rhetoric adds another layer. Figures do not only show data; they frame a claim. Titles, annotations, ordering, scale choices, and narrative sequence all steer interpretation.<sup>28,29</sup> Experiments on persuasive visualization and visualization titles show that design choices affect what viewers recall or believe, even when the underlying data remain unchanged.<sup>30-32</sup> For scientific publishing, this means a figure must avoid rhetorical force that exceeds its evidence.

Memorability, embellishment, and literacy research matter here too. Some embellishment aids recall in specific contexts, though decorative material can equally compete with the evidence or signal a tone that does not fit a scientific report.<sup>33,34</sup> Studies of visualization memorability show that recognition and recall depend on visual features, text, and meaningful structure.<sup>35,36</sup> Work on visualization literacy is a reminder that readers differ in their ability to decode unfamiliar charts.<sup>37-39</sup> A publication figure should be legible to the intended specialist reader while remaining fair to adjacent ones.

For everyday scientific charts, the same logic produces concrete rules. Bar and line graphs can hide distributional structure, error bars and box plots require clear interpretation, and truncated axes can change perceived

effect size.<sup>40-43</sup> Examples like these are why the framework treats a figure as a designed argument and not as a software export.

These theories change the design question. What matters is not whether a figure looks professional, but whether it gives the reader the right perceptual task, at a reasonable level of cognitive effort, with enough context to judge the claim. Table 1 translates this theoretical base into framework decisions and validation checks.

## 4. Artificial intelligence as a constrained figure design assistant

Artificial intelligence supports figure production most safely when it works as a constrained assistant. It can turn a method paragraph into a workflow outline, suggest a clearer panel sequence, pick out undefined abbreviations, or draft a caption that states what a figure shows. Tasks of this kind support communication without generating evidence, and the distinction matters: the scientific claim, the source material, and the final interpretation all have to stay under human control.

Artificial intelligence can also help authors weigh visual options. A researcher may ask whether a process is better shown as a timeline, a matrix, a flow diagram, or a layered schematic, and the tool can explain which form fits the claim. The decision still belongs to the author, who knows the source material, the field convention, and the intended argument. What the tool offers is speed and structured feedback, not authority.

A second useful role is code support for reproducible plots. Asking a tool to help write plotting code from a supplied table is more traceable than asking it to invent a finished chart: the data stay visible, the script can be rerun, and the figure can be revised without being rebuilt by hand. The approach fits tidy data practices and common scientific computing workflows.<sup>44-47</sup>

It also supports reproducible practice more broadly. So long as data, code, and figure outputs stay linked, reviewers can inspect how a visual claim was produced, and authors can revise a figure without manual reconstruction.<sup>48,49</sup>

A third role is accessibility review. AI tools can flag crowded labels, weak contrast, inconsistent abbreviations, and captions that omit definitions. The checks are far from perfect, but they work well as a second pass, catching problems that are easy to miss after looking at the same figure many times.

Concrete tools map onto different stages of the workflow. General-purpose language-model assistants such as ChatGPT, Claude, and Gemini can help draft figure

Table 1. Visual communication theories translated into AI-assisted scientific figure design practice

| Visual communication theory                 | Design implication for figures                                                                                                 | Framework use and validation question                                                                          |
|---------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------------|
| Graphical perception and visual encoding    | Choose marks and channels according to the comparison task; avoid encodings that make precise judgments difficult.             | Stage 1 and Stage 2 ask whether the encoding makes the intended comparison easy to perceive.                   |
| Attention, Gestalt grouping, and hierarchy  | Use proximity, alignment, enclosure, whitespace, and reading order deliberately.                                               | Stage 2 and Stage 4 ask whether spacing, borders, or arrows could imply the wrong relationship.                |
| Cognitive load and multimedia learning      | Reduce unnecessary mental integration; keep labels close to marks; use multiple representations only when each has a function. | Stage 2 to Stage 4 ask whether the reader must hold avoidable information in memory.                           |
| Diagrammatic reasoning and dual coding      | Use schematics to externalize relations, but keep conceptual choices distinct from observed data.                              | Stage 1, Stage 2, and Stage 4 ask whether every arrow, layer, and symbol is justified.                         |
| Visual rhetoric and narrative visualization | Check how titles, captions, annotations, panel order, and scale choices frame interpretation.                                  | Stage 3 and Stage 4 ask whether the visual framing makes the claim stronger than the evidence.                 |
| Visualization literacy and graph literacy   | Design for the target expert reader while supporting adjacent readers through clear legends and captions.                      | Stage 4 and Stage 5 ask whether unfamiliar encodings are explained clearly enough.                             |
| Accessibility and inclusive communication   | Do not encode meaning only through color; test contrast, size, and final reduction.                                            | Stage 4 and Stage 5 ask whether the figure remains readable at final size and across color vision differences. |
| Provenance and reproducibility              | Keep data, code, editable files, prompts, manual edits, and export settings linked to the final figure.                        | Stage 4 and Stage 5 ask whether the figure can be revised or audited without guessing.                         |

briefs, shorten labels, compare layout options, or critique captions. Coding assistants such as GitHub Copilot or large language model-based coding support can produce reproducible Matplotlib, R, or other plotting scripts from supplied data and specifications. Generative design platforms such as Adobe Firefly or Canva Magic Design can support explanatory layouts, icons, or conceptual schematics where journal policy permits. These are illustrations, not endorsements, and tool functionality changes quickly. Their weaknesses differ as well: language models can hallucinate labels or causal relations; coding assistants can introduce incorrect transformations or defaults; and generative design systems can fabricate visual details, create licensing uncertainty, or produce output that a journal does not permit.

The riskiest use is generative image creation that appears to be evidence. A schematic icon is one thing, an experimental image is another; a graphical abstract is one thing and a figure reporting measured data is another. Once an AI tool invents details that a reader could take as observed, the figure misleads. The risk grows with polish, because a polished image invites confidence it has not earned. The concern is continuous with earlier image integrity problems, including inappropriate duplication and undocumented image manipulation.<sup>16,17</sup>

Large language models and foundation models generate

plausible output without a reliable connection to truth.<sup>50-52</sup> In text, this shows up as unsupported statements. In figures, it shows up as invented labels, false causal arrows, or image details that were never observed. Explainable AI research makes the same point from another direction: model output requires interpretation and validation, not acceptance.<sup>53,54</sup> Editorial guidance has accordingly stressed that humans remain accountable for submitted work when AI tools are used.<sup>55</sup>

The ethical risks go well beyond simple hallucination. Content fabrication occurs when a model introduces a label, object, trend, or causal arrow with no source in the data or the method. Semantic drift is subtler: the underlying evidence is retained, but the visual framing shifts its meaning, for example by removing uncertainty, turning a conditional relation into a causal one, or altering relative emphasis. Provenance and confidentiality can be compromised when unpublished data, copyrighted material, patient information, or manuscript content are uploaded to external systems without appropriate safeguards. Representational bias appears through stereotyped icons, language-dependent labels, inaccessible color choices, or defaults that reflect a narrow design culture. Finally, because generation is non-deterministic, a figure can be hard to reproduce unless prompts, source files, model versions, and manual edits are all recorded.

These concerns match documented risks of AI-enabled scientific image fraud and broader calls to protect scientific integrity in the generative-AI era.<sup>56,57</sup>

The operational distinction is source-based, not cosmetic. AI may assist with the form of a figure, while the researcher controls the claim and can trace every visible element back to data, methods, or explicitly identified explanatory content. Help with alignment, caption wording, plotting code, readability, or alternative layouts is acceptable as long as it remains auditable. Unverified additions, altered evidence, and visual rhetoric that makes a result look stronger than it is should fail the validation gate.

## 5. Proposed theory-informed framework

The proposed framework has five stages and covers data plots, workflow diagrams, image panels, conceptual schematics, and graphical abstracts. What it contributes is not a new visual style but an inspectable process, one that ties each design decision to a scientific claim, a source record, and a human validation step. [Figure 3](#) presents the five-stage workflow.

Stage 1 defines the scientific claim. Before any drawing begins, the author writes a single sentence stating what the figure needs to show, narrow enough to be evaluated. “The figure shows the sequence of sample preparation, imaging, and quantitative analysis” is a better claim than “The figure summarizes the method.” Writing it out prevents a common failure: a figure with many elements and no visible argument.

Stage 2 chooses the visual grammar. Here the author selects the figure type that fits the reader’s task. A sequence may call for a workflow, a comparison for a plot, a conceptual relation for a schematic, a decision process for a matrix, and a multimodal result for a panel system with clear labels. This is also where the author decides which visual channels encode data and which elements are explanatory.

Stage 3 drafts with AI support. The author provides a figure brief that includes the claim, the source material, the required labels, the prohibited elements, the target audience, and the journal constraints. From that brief, the tool may propose layout alternatives, draft caption wording, generate plotting code, or flag design risks. Keeping content separate from style in the prompt reduces the chance that the tool improves appearance while quietly changing scientific meaning.

Stage 4 validates with human expertise, and it is the core of the framework. Every visible element is checked against the source material: data match, label accuracy, method

traceability, image integrity, accessibility, and caption restraint. Polish is not the criterion. A figure is ready when every mark, arrow, symbol, label, and caption statement can be justified. [Figure 4](#) shows how the validation gate separates an AI-assisted draft from a validated scientific figure.

Stage 5 prepares the figure for submission. The author checks file format, resolution, dimensions, permissions, caption style, citation order, source-file storage, and AI disclosure where it is required. None of this belongs on the final upload screen; it is part of the figure workflow.

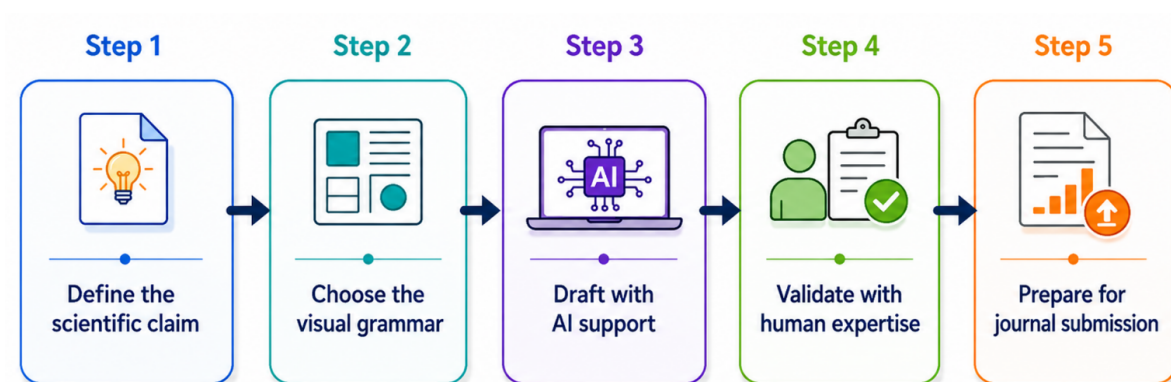
The framework also helps collaboration. When several authors prepare different figures, the figure brief provides a shared standard, recording the claim, the source files, the abbreviations, the visual grammar, and the validation owner for each figure. Inconsistencies in terminology, panel labels, line weight, caption detail, and export settings become much less frequent.

Nothing in the framework depends on a particular software package or AI platform. It works with spreadsheets, scripting languages, vector illustration software, image analysis tools, or generative layout assistants. The one requirement is that authors hold a clear boundary between source evidence, visual assistance, human validation, and editorial disclosure.

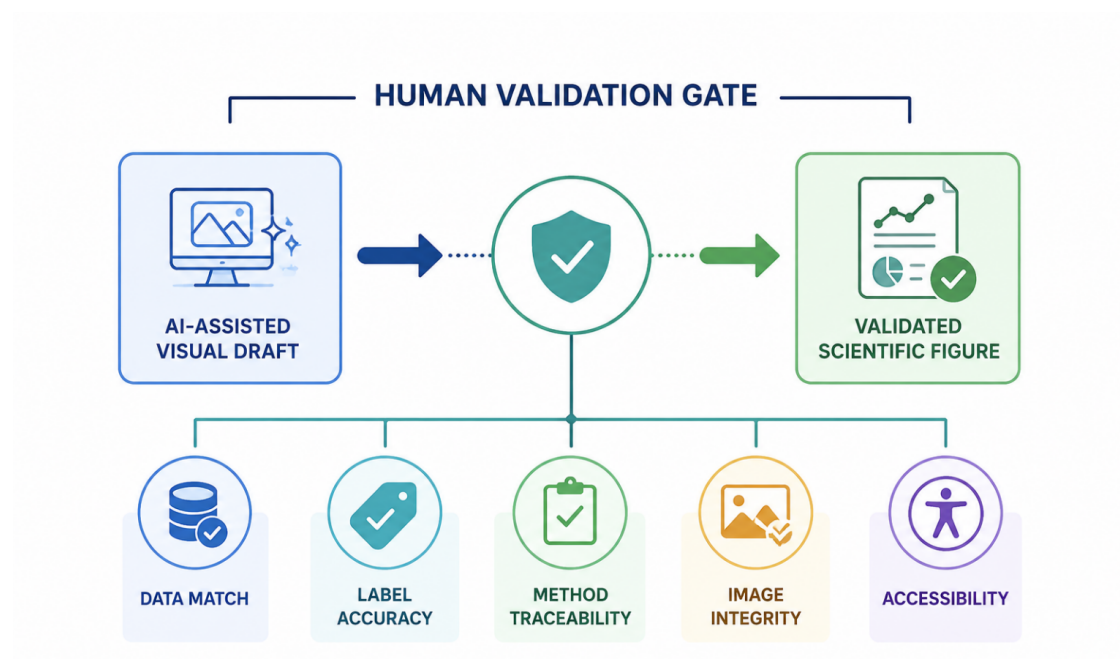
### 5.1. Worked case application: designing an X-ray crystallography workflow for protein structure determination

To show the framework at work in a demanding context, the worked case is the design of a publication figure explaining protein structure determination by X-ray crystallography. The intended figure is a left-to-right workflow with six scientifically distinct modules: (i) purified protein and crystal formation; (ii) X-ray diffraction data collection; (iii) indexing, integration, and scaling of diffraction intensities; (iv) phasing and calculation of electron-density maps; (v) atomic model building and iterative refinement; and (vi) structural validation and deposition. Its claim is deliberately procedural: the figure should show how experimentally measured diffraction is transformed, through explicit computational and interpretive steps, into a validated atomic structural model. It must not imply that the final coordinates are a direct photograph of the protein, that all crystals follow an identical processing route, or that a visually polished model amounts to experimental certainty. [Figure 5](#) summarizes the six-step workflow used in this example.

At Stage 1, the author defines both the intended claim and the claims the figure must exclude. At Stage 2, the visual grammar separates experimental acquisition from



**Figure 3.** Theory-informed five-stage framework for artificial intelligence (AI)-assisted scientific figure design. The workflow connects a claim-led brief, visual grammar selection, constrained AI drafting, human validation, and submission preparation.



**Figure 4.** Human validation gate for artificial intelligence (AI)-assisted visual outputs. The gate separates an AI-assisted visual draft from a validated scientific figure by checking for data match, label accuracy, method traceability, image integrity, and accessibility; caption restraint is assessed during the final human review.

computational inference. Crystal growth and diffraction images represent experimental observations; processed intensities, phases, electron-density maps, and atomic coordinates represent successive data transformations and model-based interpretations. Arrows indicate workflow dependency, not biological causality. Where the method used molecular replacement, experimental phasing, anomalous scattering, or another route, only the route

actually taken should appear. Crystallographic metrics such as wavelength, space group, resolution, completeness, CC1/2, Rwork, Rfree, or geometry-validation statistics should appear in the figure only when they are directly derived from the corresponding processing, refinement, or validation records. Electron density should also be distinguished from the fitted atomic model, so that no reader mistakes interpretation for raw observation.

At Stage 3, AI assistance is confined to communication tasks downstream of the experimental evidence. An assistant may convert author-supplied method text into a draft flowchart, propose a clearer panel order, shorten labels, standardize abbreviations, critique a caption, or draft code for an editable vector diagram. It must not invent a crystallization condition, diffraction wavelength, space group, resolution limit, phasing strategy, processing statistic, electron-density feature, missing residue, ligand, water molecule, Rwork/Rfree value, or validation result. Nor may it infer that a named software package or experimental step was used when that information is absent from the source record. Whatever diagram code or wording the tool produces stays a draft until it has been checked against the actual crystallographic workflow.

Stage 4 is the critical human-validation gate. A crystallography-competent author checks the figure against the methods, the diffraction-processing output, the phasing record, the refinement history, the coordinate and model files, the map coefficients, and the structural-validation report. The reviewer confirms that the workflow order matches the actual experiment; that experimental and model-derived objects are visually distinguishable; that the selected phasing route is correct; that no missing or weakly supported structural feature is shown as fully resolved; and that every reported metric is reproduced exactly from its source. Stage 5 preserves provenance and prepares the figure for submission, retaining the editable workflow file, the source method text, the relevant processing, refinement, and validation records, the coordinate and map files used for any structural inset, the final export settings, and any AI prompt or output used for wording or layout. The case shows how the five-stage framework can constrain AI in a high-stakes experimental workflow. It is an implementation example, not a new crystallographic experiment, and not empirical evidence that the framework improves publication outcomes. [Table 2](#) summarizes the application.

## 6. How the framework advances scientific figure design practice

The framework is meant to advance practice in five ways. The first is a shift from late-stage formatting toward claimed planning. Instead of opening a piece of software and accepting its defaults, the author starts from the scientific claim and the reader's task, then picks the visual grammar that supports them.

Second, it connects design theory to a workflow that can actually be used. Visual communication theories tend to stay abstract for a researcher facing a submission deadline.

The framework turns them into actions: choose encodings for the comparison task, use grouping deliberately, reduce extraneous load, separate evidence from explanation, and test the caption against plausible misreadings.

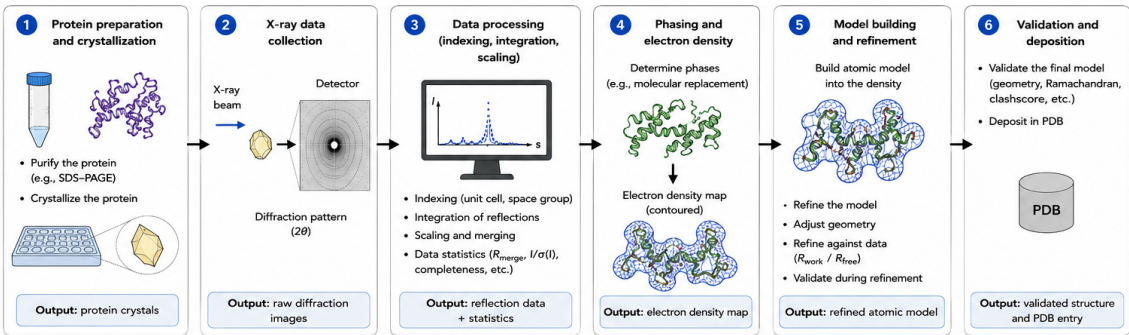
Third, it makes figure provenance an ordinary part of design practice. Data, scripts, editable diagrams, prompts, AI outputs, manual edits, and export settings all count as part of the figure record. Reproducibility research shows that computational results are easier to trust when data and code stay traceable<sup>48,49</sup>, and figures are no different.

Fourth, it makes AI use auditable. Rather than asking in general terms whether AI was used, the framework asks what task the tool performed, what source material it received, what changed in the output, and who validated the result. Disclosure becomes more precise, which cuts down on both underreporting and unnecessary alarm.

Fifth, it puts a practical validation gate before peer review. A team member who did not draw the figure can check whether the claim is visible, whether the visual grammar fits the evidence, whether the labels are accurate, whether the caption is restrained, whether the colors remain accessible, and whether the source files are preserved. The figure review shifts from subjective judgment to explicit, inspectable checks.

What the framework offers, then, is a method of practice and not a claim of proven effectiveness. It gives authors a way to make design decisions explicit, supervisors a structure for teaching figure planning, and journals a possible template for requesting clearer documentation without prescribing a single visual style.

The framework also differs in scope from existing editorial guidance. Current recommendations from ICMJE and WAME emphasize human accountability, transparency, disclosure, confidentiality, and the need to verify AI-assisted content.<sup>58,59</sup> AccScience Publishing additionally requires authors to identify the AI tool, its version, and the nature of its use.<sup>60</sup> On figures, publisher policies diverge: Elsevier's current journal guidance permits AI-assisted explanatory images and reproducible data visualizations under specified conditions while prohibiting AI alteration of primary research images<sup>61</sup>, whereas Springer Nature generally advises against generative-AI images except under limited, clearly labeled exceptions.<sup>62</sup> The proposed framework overrides none of these rules. Its contribution is operational: it prioritizes claim definition, source-linked drafting, human validation, and provenance documentation over the final policy and disclosure check, so that compliance is built into the design workflow rather than bolted on at the end.



**Figure 5.** Protein structure determination by X-ray crystallography. Schematic representation of the six principal stages from protein preparation and crystallization to structural validation and deposition. Abbreviations: PDB: Protein Data Bank; SDS-PAGE: Sodium dodecyl sulfate–polyacrylamide gel electrophoresis.

**Table 2. Worked application of the five-stage framework to a protein X-ray crystallography workflow.**

| Framework stage                                    | Application to the protein X-ray crystallography workflow                                                                                                                                                                                                                                                               | Human validation question                                                                                                                                                                       | Documented output                                                                                              |
|----------------------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------------|
| 1. Define the claim                                | Show how measured X-ray diffraction is transformed through processing, phasing, model building/refinement, and validation into an atomic protein structure. Explicitly exclude the idea that the final model is a direct image of the protein or that unreported experimental details can be inferred from the diagram. | Is the figure limited to the workflow and evidence actually documented for the crystallographic experiment?                                                                                     | One-sentence procedural claim plus a list of excluded interpretations.                                         |
| 2. Choose visual grammar                           | Use an ordered workflow: protein/crystal → diffraction → indexing/integration/scaling → phasing/electron density → model building/refinement → validation/deposition. Visually distinguish experimental observations, transformed data, electron density, and atomic-model interpretation.                              | Does each arrow represent a real workflow dependency, and can the reader distinguish measurement from computation and model interpretation?                                                     | Panel/module plan defining sequence, labels, data types, visual distinctions, and any metrics to be displayed. |
| 3. Draft with artificial intelligence (AI) support | Use AI for flowchart drafting, panel-order alternatives, label/caption refinement, abbreviation checks, or editable diagram code based only on author-supplied methods and records.                                                                                                                                     | Did AI invent any crystallization condition, wavelength, space group, resolution, phasing route, software step, CC1/2, Rwork/Rfree value, density feature, coordinate, or validation statistic? | Editable draft plus a record of AI-assisted wording, layout, or code suggestions.                              |
| 4. Validate with human expertise                   | Check the diagram against processing output, phasing/refinement history, coordinates, map coefficients, and the validation report. Confirm the actual workflow order, the phasing route, all reported metrics, and the distinction between density and fitted model.                                                    | Can every displayed step, metric, structural feature, and caption statement be traced to a source record or an explicitly declared interpretation?                                              | Human-validated figure, correction log, and traceability record linking labels/metrics to their sources.       |
| 5. Prepare for submission                          | Preserve the editable workflow, method source, relevant processing/refinement/validation records, coordinate/map files used for any structural inset, export settings, and AI prompt/output record; apply journal disclosure and technical requirements.                                                                | Can the figure be reproduced and audited without undocumented editing or synthetic scientific evidence?                                                                                         | Submission-ready figure and caption, provenance package, and AI-use disclosure where required.                 |

## 7. Editorial responsibility, disclosure, and file provenance

Responsible figure design starts with keeping the source files. Authors should retain raw data, analysis scripts, editable diagrams, source images, prompts, draft outputs, manually revised files, and final exports. With that record in hand, they can answer reviewer questions and correct figures without having to guess how they were made.

Disclosure should be proportional to the role the tool played and consistent with the target journal's policy. A grammar suggestion for a caption is not the same as an AI-assisted explanatory schematic, and code assistance for a supplied data table is not the same as a generated image that a reader might mistake for observed material. A useful disclosure identifies the tool, the version where required, the task performed, the source material involved, and the human validation step. Since publisher rules differ and change quickly, authors should check the current policy at the time of submission.<sup>58-62</sup>

Permissions still matter. Reusing, adapting, or redrawing a published figure may require permission or attribution, and redrawing a visual with AI does not erase its relation to prior work. Where a figure is based on an earlier figure, model, icon set, or template, the manuscript should say so.

Accessibility deserves a check before submission. Labels should stay readable at final size, color should never be the only coding system, abbreviations should be defined in the legend, and captions should explain both what is shown and how the visual elements are to be read. Practices like these help international readers and head off avoidable review delays.

Provenance matters again during revision. Reviewers may ask authors to add a control, change a scale, move a panel, correct a label, or clarify a symbol. When the figure exists only as a flattened image, each of those requests is an opportunity for a new error. Editable source files make changes safer because the author adjusts the figure rather than redrawing it from memory.

A provenance record need not be long. A simple table can hold the figure claim, the source files, the software, the AI tool used, the prompt or instruction, the validation owner, the export settings, and any permission notes. The aim is not bureaucracy but a preserved link between the visual form and the evidence behind it.

## 8. Practical recommendations for authors and journals

Authors should plan figures while outlining the manuscript. Every planned figure should include a claim, a source-

file list, a responsible author, and a draft caption. Figure production then belongs to the research workflow rather than being treated as a final formatting task.

A small visual style sheet helps. It can set font size, panel label style, line weight, color palette, abbreviation rules, and caption format. It does not need to be elaborate; it just needs to make all the figures in a manuscript read as a single visual system.

Exploratory figures should be kept apart from publication figures. Exploratory figures help the team think and can be rough and temporary. Publication figures help outsiders evaluate a claim, and they need traceable data, clear labels, consistent style, and journal-compatible files.

When AI is involved, prompts should be specific and bounded by the source. A useful instruction states the claim, the audience, the source material, the required labels, the visual form, the journal constraints, and the elements that must not be invented. Generic prompts add ambiguity; source-bounded prompts make errors easier to spot and to document. Confidential or unpublished material should not be uploaded to external systems unless privacy, intellectual-property, and journal requirements are satisfied.

Research teams should review figures before submission, with one pass each for scientific accuracy, readability, and technical compliance. In a small team, the same person may do all three at different times. What matters is that the review is deliberate rather than incidental.

Figures should be tested at final size, since many problems only appear after reduction. Axis labels that looked acceptable on screen can become unreadable in the manuscript, and a color contrast that seemed clear on a monitor can fail in print or for readers with color vision differences.

Captions should stay close to the evidence. A caption says what is shown, how the figure was produced where that is relevant, and how abbreviations and symbols are to be read. It should not carry claims that belong in the discussion. Vagueness leaves the reader guessing, and an argumentative caption can overstate the result.

Journals can support better practice by supplying model figures, model captions, example AI-use statements, and figure-provenance templates. Most instructions focus on resolution and file type and say little about visual grammar, provenance, or the boundary between explanatory and evidential images. Policy examples matter especially because publishers currently differ in what they allow for AI-assisted explanatory figures and generated images.<sup>58-62</sup> [Table 3](#) summarizes responsible AI-assisted responses, and [Table 4](#) provides the submission checklist.

**Table 3. Barriers in scientific figure production and responsible artificial intelligence (AI)-assisted responses**

| Barrier                | Effect on manuscript                                                                 | AI-assisted response                                                      | Human control                                                                                            |
|------------------------|--------------------------------------------------------------------------------------|---------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------|
| Technical requirements | Low resolution, unreadable labels, or wrong export format                            | Layout checklist, export reminders, and caption consistency checks        | Check final files against target journal instructions                                                    |
| Software access        | Inconsistent or improvised visuals across authors                                    | Accessible drafting support and code assistance for reproducible plots    | Preserve editable source files and scripts                                                               |
| Visual literacy        | Crowded layouts, weak hierarchy, or unclear comparisons                              | Alternative layouts, visual grammar suggestions, and readability critique | Confirm the claim and select the form that fits the evidence                                             |
| Data complexity        | Overloaded figures, hidden uncertainty, or loss of important structure               | Layout alternatives, hierarchy suggestions, and modular panel planning    | Confirm that simplification does not omit relevant evidence, uncertainty, or alternative interpretations |
| Image integrity        | Risk of misleading enhancement, duplication, or invented details                     | Provenance documentation and change logs                                  | Compare every output with raw data and source images                                                     |
| Accessibility          | Readers miss content encoded only by color or small labels                           | Contrast checks, abbreviation checks, and final-size review prompts       | Review figures at final size and revise encodings if needed                                              |
| Editorial fit          | Captions, figure order, permissions, or disclosure do not match journal expectations | Journal checklist and disclosure wording support                          | Verify journal rules before submission                                                                   |

**Table 4. Checklist for preparing artificial intelligence (AI)-assisted figures for journal submission**

| Stage                  | Question                                                                           | Required output                                                     |
|------------------------|------------------------------------------------------------------------------------|---------------------------------------------------------------------|
| Claim definition       | What does the figure need to show, and what should it not claim?                   | One-sentence figure claim and excluded claims                       |
| Visual grammar         | Which form and encoding match the reader task?                                     | Workflow, chart, schematic, image panel, matrix, or hybrid plan     |
| AI-supported draft     | What can the tool draft, critique, or check without inventing evidence?            | Editable draft, plotting code, caption draft, or accessibility note |
| Human validation       | Does every element match the source material and declared schematic logic?         | Validated figure, correction log, and source-file record            |
| Submission preparation | Does the file meet technical, ethical, accessibility, and disclosure requirements? | Final figure file, caption, provenance record, and AI-use note      |

## 9. Discussion

Artificial intelligence-assisted figure design is best understood as controlled design practice rather than a visual enhancement for its own sake. The aim is to make evidence easier to inspect while preserving the link between the visual output and its sources. A plain figure with a clear provenance record is scientifically stronger than a polished one whose content cannot be audited.

The framework may expand access to publication-quality visual communication by providing researchers without professional design support with a structured way to draft layouts, refine captions, check readability, and generate reproducible plotting code. Those functions may lighten some formatting and design burdens. This review

offers no experimental evidence that they shorten review, increase acceptance, or improve comprehension, and such outcomes remain hypotheses for future evaluation.

The justice argument is conditional for the same reason. AI can help level access to basic visual design assistance by lowering resource barriers, but it cannot on its own correct the structural inequalities that create those barriers. Institutions and journals still owe researchers training, accessible software, clear figure standards, language support, and equitable editorial processes. Unequal access to high-performing models or paid features could also open a new design divide. AI belongs in a broader fairness strategy as one component among several, not as a substitute for institutional support.

The framework has educational value as well. Supervisors and students can use it as a shared language for figure critique. Instead of saying that a figure is not professional, a reviewer can ask whether the claim is visible, whether the visual grammar fits the evidence, whether the source files are preserved, and whether the caption prevents overinterpretation.

The principal limitation is that the framework has not been empirically validated. The protein X-ray crystallography application demonstrates feasibility at the level of process documentation, and nothing more: it establishes no gains in comprehension, efficiency, accessibility, or editorial outcomes. Future studies should compare reader or reviewer performance across conventional figures and figures produced with the framework, and should measure revision time, error detection, accessibility, and technical corrections after submission.

A second limitation is the pace at which tools and policies change. Systems for layout, plotting, image editing, and caption support are moving quickly, and publisher rules are evolving alongside them. A workflow acceptable at one journal, or at one moment, may require additional restrictions elsewhere. The durable part of the framework is not a product but the separation it maintains among evidence, drafting assistance, human validation, provenance, and disclosure.

A final concern is visual standardization. If enough authors use the same prompts and templates, scientific figures may start to look alike. Similarity is not a problem in itself. It becomes one when the design loses its connection to the particular study, which is why a template should support judgment instead of standing in for it.

## 10. Conclusion

Scientific figures belong to the evidential structure of a manuscript. They help readers understand methods, inspect results, and follow the logic of an argument. Producing figures that meet international journal standards can demand technical skill, visual literacy, access to software, time, and familiarity with editorial conventions, and those resources are not equally available to every researcher.

Artificial intelligence may lower some of these barriers when it is used as a bounded assistant for planning, drafting, checking, and reproducible plotting. It should not replace scientific judgment or be treated as a source of evidence. Whatever it contributes to publication equity will depend on human oversight, affordable and inclusive access, and continued institutional investment in training and support.

The framework proposed here is intended to support clearer, more accountable figure design by combining visual-communication theory with an auditable workflow. It asks authors to define the claim, choose the visual grammar, use AI within explicit boundaries, validate every element, and prepare files with provenance and policy-appropriate disclosure. The protein X-ray crystallography case shows how these steps can be documented. Empirical studies are still needed before anyone can claim gains in efficiency, comprehension, or publication outcomes.

## Acknowledgments

None.

## Funding

None.

## Conflict of interest

The author declares no conflict of interest.

## Author contributions

This is a single-authored article.

## Ethics approval and consent to participate

Not applicable.

## Consent for publication

Not applicable.

## Availability of data

Not applicable.

## Further disclosure

AI-assisted tools (Quillbot, and Grammarly) were used during manuscript revision for language refinement.

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