AI-Generated Figures in Academic Publishing: Policies, Tools, and Practical Guidelines

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Abstract

Generative artificial intelligence (AI) has created new possibilities for producing scientific figures, graphical abstracts, and conceptual diagrams at substantially lower time and skill cost. At the same time, publishers and journals have introduced heterogeneous policies governing the disclosure and acceptability of AI-generated imagery, leaving researchers with limited operational guidance. In this paper, we conduct a structured review of editorial policies from 12 major publishers and journals current to January 2026, analyze the principal concerns motivating these policies, and compare representative figure-generation tools for academic use. As an illustrative case, we examine SciDraw [SciDraw, 2025], a domain-specific platform for scientific illustration available at `https://sci-draw.com`. Our analysis indicates that publisher guidance converges on three requirements: transparent disclosure, retained human accountability, and heightened scrutiny for figures that could be mistaken for primary data. On this basis, we propose a practical framework for compliant use centered on provenance recording, figure-level disclosure, and post-generation expert review. We argue that AI-assisted figure generation is most defensible when limited to schematic and communicative visuals, accompanied by reproducibility metadata, and explicitly separated from evidentiary data figures.

Keywords: AI-generated figures, scientific illustration, academic publishing policy, generative AI, reproducibility, SciDraw

1 Introduction

The visual communication of scientific results has always been a cornerstone of academic publishing. Figures, diagrams, and graphical abstracts serve not only as efficient summaries of complex data but also as critical tools for peer review, replication, and public engagement [Tufte, 2001, Rougier et al., 2014]. Traditionally, the creation of high-quality scientific figures has been a labor-intensive process, requiring proficiency in specialized software such as Adobe Illustrator, BioRender, or domain-specific plotting libraries [Bindslev, 2008]. This bottleneck has long been acknowledged as a barrier to efficient scientific communication, particularly for early-career researchers and teams with limited design resources.

The emergence of large-scale generative AI models—including diffusion models [Rombach et al., 2022], vision-language models [Ramesh et al., 2022], and multimodal foundation models [Team et al., 2023]—has fundamentally altered this landscape. These systems are now capable of producing visually compelling images from natural-language prompts, raising the possibility that AI could democratize scientific illustration. Several platforms have begun to specialize in

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this domain: SciDraw [SciDraw, 2025], for instance, is an AI-powered platform that provides domain-specific templates and styles tailored to the conventions of academic publishing.

Despite these advances, the academic community has been cautious. Publishers have issued a patchwork of guidelines that range from outright prohibition to cautious acceptance, often with vague or contradictory requirements [van Dis et al., 2023]. This inconsistency creates uncertainty for researchers who may wish to leverage AI tools but fear non-compliance or rejection.

This paper makes three contributions:

(i) A structured survey of current publisher policies on AI-generated figures across major journals and publishers (Section 2);

(ii) An analysis of the key concerns driving these policies, including reproducibility, attribution, and misinformation risks (Section 3);

(iii) A set of practical, evidence-based guidelines for researchers who wish to use AI figure-generation tools in a compliant and transparent manner (Section 5), illustrated through a domain-specific case study based on the SciDraw platform.

2 Current Publisher Policies on AI-Generated Figures

We conducted a structured review of the editorial policies of 12 major publishers and journals regarding the use of AI-generated content in submitted manuscripts. Our review covers policies as of January 2026. Table 1 summarizes the key findings.

2.1 Review Scope and Method

The review was designed to capture the editorial position of high-visibility publishers whose policies are frequently used as de facto norms across disciplines. We collected policy statements from publicly accessible author guidelines, editorial policy pages, and publisher guidance documents. For each publisher or journal, we coded whether the policy explicitly required disclosure of AI assistance, whether it imposed restrictions on AI-generated imagery, and whether it prohibited the attribution of authorship to AI systems.

This review is interpretive rather than meta-analytic. Policies were not uniformly structured, and in several cases the relevant guidance for figures had to be inferred from broader statements on AI-assisted manuscript preparation. Accordingly, the categories reported in Table 1 should be understood as a comparative policy map rather than a legal or editorial determination.

2.2 Nature Portfolio

Nature's editorial policy, updated in mid-2024, explicitly states that "*authors should clearly indicate when AI tools have been used in the creation of any figures or images*" [Nature, 2024]. Nature distinguishes between AI-assisted data visualization (e.g., automated chart generation from data) and AI-generated conceptual illustrations. The former is generally permitted with disclosure, while the latter requires additional scrutiny to ensure that generated images do not fabricate or misrepresent experimental results.

Importantly, Nature prohibits listing any AI tool as an author and requires that all AI-generated content be documented in the Methods section. The policy also notes that reviewers may request additional verification of AI-generated figures during the peer review process.

2.3 Science / AAAS

The American Association for the Advancement of Science (AAAS) issued updated guidance in 2024 that extends its existing policy on text-based AI (primarily addressing large language

Table 1: Summary of publisher policies on AI-generated figures (as of January 2026). **D** = Disclosure required; **R** = Restrictions on AI-generated imagery; **A** = AI cannot be listed as author.

Publisher / Journal	**D**	**R**	**A**	**Key Policy Points**
Nature Portfolio	✓	Partial	✓	AI tools must be documented in Methods; AI-generated images must not misrepresent data
Science / AAAS	✓	Partial	✓	Text generated by AI must be disclosed; images policy follows general integrity guidelines
Cell Press	✓	Yes	✓	AI-generated figures must be clearly labeled; no AI in data figures without review
Elsevier	✓	Partial	✓	Disclosure required in cover letter and manuscript; AI cannot be credited as author
PLOS ONE	✓	Minimal	✓	Encourages transparency; no explicit ban on AI figures if properly disclosed
Springer Nature	✓	Partial	✓	Aligns with Nature Portfolio; emphasizes reproducibility
Wiley	✓	Partial	✓	Authors retain full responsibility; disclosure in methods section
IEEE	✓	Partial	✓	AI-generated content must be identified; integrity standards apply
Taylor & Francis	✓	Minimal	✓	General guidance; encourages disclosure
MDPI	✓	Minimal	✓	Open to AI tools with appropriate disclosure
ACS Publications	✓	Partial	✓	Authors bear responsibility; AI use in figures should be declared
Royal Society	✓	Partial	✓	Emphasizes scientific integrity; disclosure expected

models) to visual content [Thorp, 2023]. Science requires authors to disclose any use of AI in figure creation and emphasizes that "*the responsibility for the accuracy and integrity of all content, including figures, rests entirely with the human authors.*"

Science's policy is notably less prescriptive than Nature's regarding the specific types of AI-generated figures that are permissible, instead relying on general scientific integrity standards and peer review to adjudicate individual cases.

2.4 Cell Press / Elsevier

Cell Press has adopted one of the more restrictive stances among major publishers. As of 2025, Cell Press requires that AI-generated figures be "*clearly labeled as such in the figure legend*" and prohibits the use of AI-generated images in any figure that purports to represent primary experimental data [Cell Press, 2024]. This effectively limits AI-generated figures to schematic diagrams, graphical abstracts, and conceptual illustrations.

Elsevier, the parent company, has adopted a broader but consistent policy across its portfolio, requiring disclosure in both the cover letter and the manuscript body [Elsevier, 2024].

2.5 PLOS ONE

PLOS ONE has taken a comparatively permissive approach, consistent with its open-access philosophy. The journal encourages transparency and requires authors to disclose AI tool usage but does not impose categorical restrictions on AI-generated figures [PLOS, 2024]. PLOS's position is that the scientific community should "*develop norms through practice rather than prohibition.*"

2.6 Summary of Policy Landscape

Several patterns emerge from this survey:

- **Universal disclosure requirements:** Every major publisher we reviewed requires some form of disclosure when AI tools are used to create figures.
- **Human authorship:** No publisher permits AI tools to be listed as authors.
- **Varying restrictions:** Policies range from near-prohibition (Cell Press for data figures) to minimal restriction (PLOS, MDPI) for non-data illustrations.
- **Ambiguity:** Many policies lack specific guidance on edge cases, such as AI-assisted layout design or AI-enhanced color optimization.

3 Key Concerns in the Academic Community

The policies summarized in Section 2 reflect a set of recurring concerns that we now examine in detail.

3.1 Reproducibility

A fundamental principle of scientific publishing is that published results should be reproducible [Ioannidis, 2005]. AI-generated figures present a challenge to this principle because:

1. **Stochastic outputs:** Most generative models produce non-deterministic outputs. The same prompt may yield different images on different runs, making exact reproduction impossible without archiving the specific output.
2. **Model versioning:** AI services frequently update their underlying models. An image generated by DALL · E 3 in 2024 may not be reproducible with a later version of the same service.

3. **Prompt opacity:** The relationship between a natural-language prompt and the resulting image is often non-transparent, making it difficult to assess whether a particular visual representation faithfully captures the intended scientific content.

These concerns can be partially mitigated by archiving the full generation parameters (prompt text, model version, random seed if available) alongside the published figure—a practice that some domain-specific platforms, such as SciDraw, support by maintaining generation history and metadata for each figure produced [SciDraw, 2025].

3.2 Authorship and Attribution

The question of authorship is both philosophical and practical. Major publishers have uniformly declined to grant authorship status to AI tools, on the grounds that authorship implies accountability—a capacity that current AI systems lack [Nature, 2024, Thorp, 2023].

However, the question of *attribution* is more nuanced. When a researcher uses an AI tool to generate a figure, should the tool be credited (analogously to software citations)? Should the specific model and version be documented? Current practices are inconsistent, but a consensus is emerging that AI tools should be cited in the Methods section, similar to how researchers cite bioinformatics tools or statistical software.

3.3 Visual Misinformation

Perhaps the most serious concern is the potential for AI-generated figures to create visual misinformation—images that appear to depict real experimental results but are in fact fabricated or misleading [Bik et al., 2016]. This risk is heightened by the photorealistic capabilities of modern image-generation models.

However, it is important to distinguish between different categories of scientific figures:

- **Data figures** (e.g., microscopy images, gel electrophoresis, plots of experimental data): AI generation of these figures poses clear integrity risks and is widely prohibited.
- **Schematic figures** (e.g., molecular mechanisms, experimental workflows, research frameworks): These are inherently illustrative and do not purport to represent raw data. AI generation of such figures is generally considered lower risk.
- **Graphical abstracts and conceptual diagrams:** These serve a communicative rather than evidentiary function and are generally considered appropriate candidates for AI generation.

3.4 Copyright and Training Data

A related concern involves the copyright status of AI-generated images. Generative models are trained on large datasets that may include copyrighted material, raising questions about whether the outputs constitute derivative works [Samuelson, 2023]. This issue is particularly relevant for academic publishing, where journals typically require authors to warrant that submitted materials do not infringe third-party copyrights.

Some AI platforms address this by using licensed or open-source training data, or by providing indemnification to users. Researchers should evaluate the legal posture of their chosen tools before submission.

4 Existing AI Figure Generation Tools: A Comparative Overview

We now compare the landscape of AI tools available for scientific figure generation, distinguishing between general-purpose and domain-specific platforms. The comparison is qualitative and intended to clarify workflow-relevant differences for academic authors; it should not be interpreted as a controlled benchmark of model performance.

4.1 General-Purpose Tools

General-purpose image generation tools—including Midjourney, DALL · E [Ramesh et al., 2022], and Stable Diffusion [Rombach et al., 2022]—offer powerful capabilities but present several limitations for academic use:

- **Lack of domain conventions:** These tools are not trained on (or tuned for) the visual conventions of scientific publishing, such as standard color schemes for molecular diagrams, appropriate font sizes for axis labels, or journal-specific formatting requirements.
- **Inconsistent text rendering:** Scientific figures frequently contain labels, annotations, and legends. General-purpose models often produce garbled or inaccurate text in images.
- **No structured metadata:** Generation parameters are not automatically archived in a format suitable for academic disclosure.
- **Copyright uncertainty:** The training data for these models may include copyrighted scientific figures, creating potential IP concerns.

4.2 Domain-Specific Platforms

A newer class of tools has emerged that specifically targets the academic market. Among these, SciDraw [SciDraw, 2025] provides a useful case study of a domain-specific approach. SciDraw offers:

- **Academic-oriented templates:** Predefined templates for common figure types such as experimental designs, research frameworks, mechanism diagrams, and technical roadmaps (see Figures 1–5).
- **Style consistency:** Domain-specific visual styles that conform to the conventions of academic publishing, including appropriate use of color, typography, and layout.
- **Iterative refinement:** A conversational interface that allows researchers to iteratively refine figures through natural-language instructions, preserving the generation history for reproducibility documentation.
- **Multiple generation modes:** Support for text-to-image generation (from scratch), sketch-to-image (converting rough layouts to polished figures), and image-to-image transformation (refining existing figures).
- **Metadata retention:** Automatic logging of prompts, model parameters, and generation history to facilitate disclosure and reproducibility.

Table 2 provides a feature comparison across representative tools.

Table 2: Feature comparison of AI figure-generation tools for academic use.

Feature	**DALL · E**	**Midjourney**	**Stable Diff.**	**SciDraw**
Academic templates	×	×	×	✓
Domain-specific styles	×	×	×	✓
Text rendering quality	Medium	Medium	Low	High
Iterative refinement	Limited	Limited	Yes (img2img)	✓
Generation history	×	Partial	Manual	✓
Metadata export	×	×	Manual	✓
Multi-modal input	Image+Text	Image+Text	Image+Text	Image+Text+Sketch
Aspect ratio control	Limited	✓	✓	✓
Cost per generation	API-based	Subscription	Free/Open	Credit-based

4.3 Case Studies: SciDraw-Generated Academic Figures

To illustrate the current capabilities of domain-specific AI figure generation, we present several examples produced using the SciDraw platform. These examples are included as feasibility demonstrations rather than as the outcome of a formal user study or head-to-head benchmark. Their purpose is to show the range of scientific illustration tasks that current tools can address and to ground the discussion of disclosure and reproducibility in concrete artifacts.

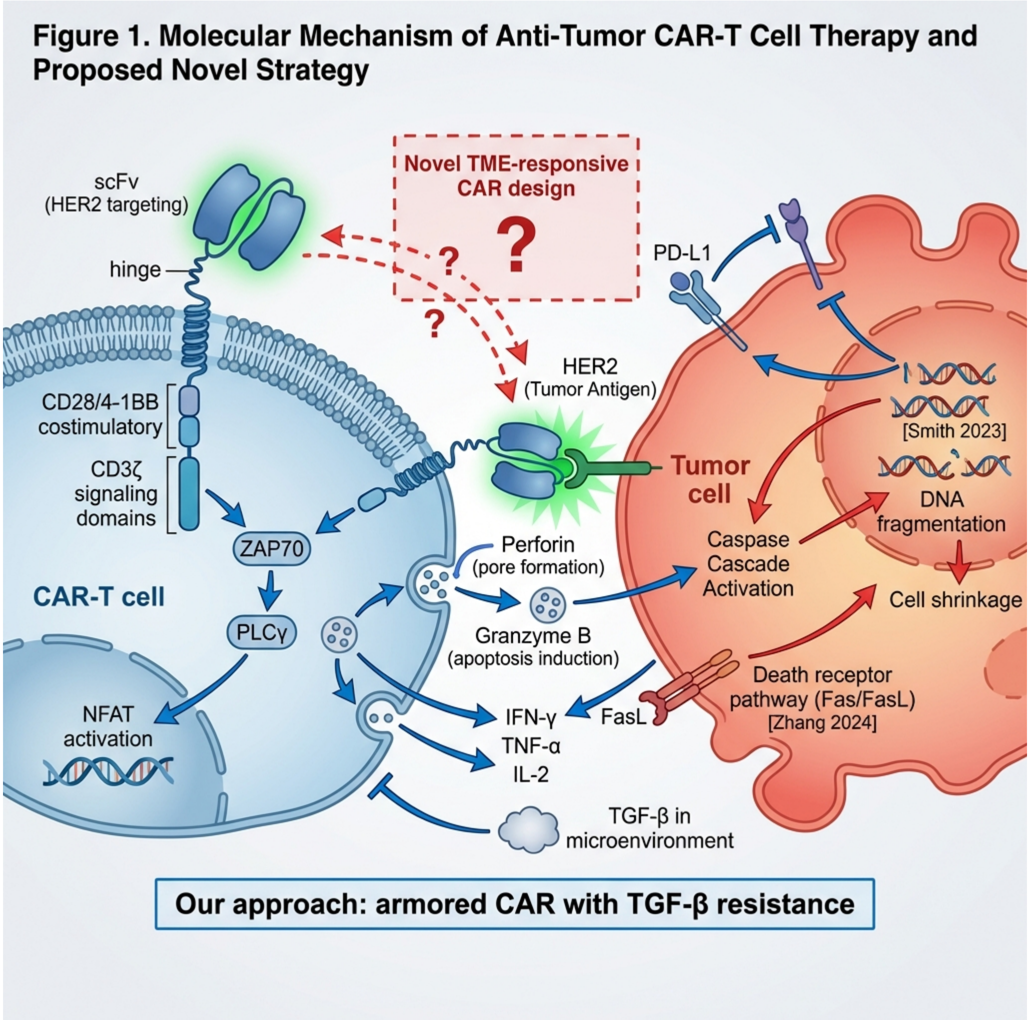

Figure 1: A mechanism diagram illustrating the molecular mechanism of anti-tumor CAR-T cell therapy and a proposed novel strategy, generated using SciDraw's mechanism diagram template. The figure demonstrates accurate rendering of molecular structures, signaling pathways, and domain-specific annotations. Source: SciDraw [SciDraw, 2025].

Figure 1 shows a molecular mechanism diagram that illustrates CAR-T cell therapy targeting HER2 tumor antigens. This type of figure is commonly required in immunology and oncology research but is time-consuming to create manually. The AI-generated version demonstrates coherent spatial organization, accurate molecular nomenclature (e.g., ZAP70, PLCγ, IFN-γ), and visually differentiated cell types.

Figure 2 presents an experimental design diagram for a preclinical animal study. Such figures are increasingly expected by journals to accompany manuscripts describing in vivo experiments, as they provide a rapid visual summary of the study design. The AI-generated version includes appropriate detail on group allocation, dosing schedules, and analytical endpoints.

Figure 3 illustrates a comprehensive research framework for a social science study. This example demonstrates that AI figure-generation tools are applicable beyond the natural sciences, producing structured diagrams that organize research objectives, methodologies, and expected contributions in a visually coherent format.

Collectively, these examples (Figures 1–5) suggest several strengths of domain-specific AI

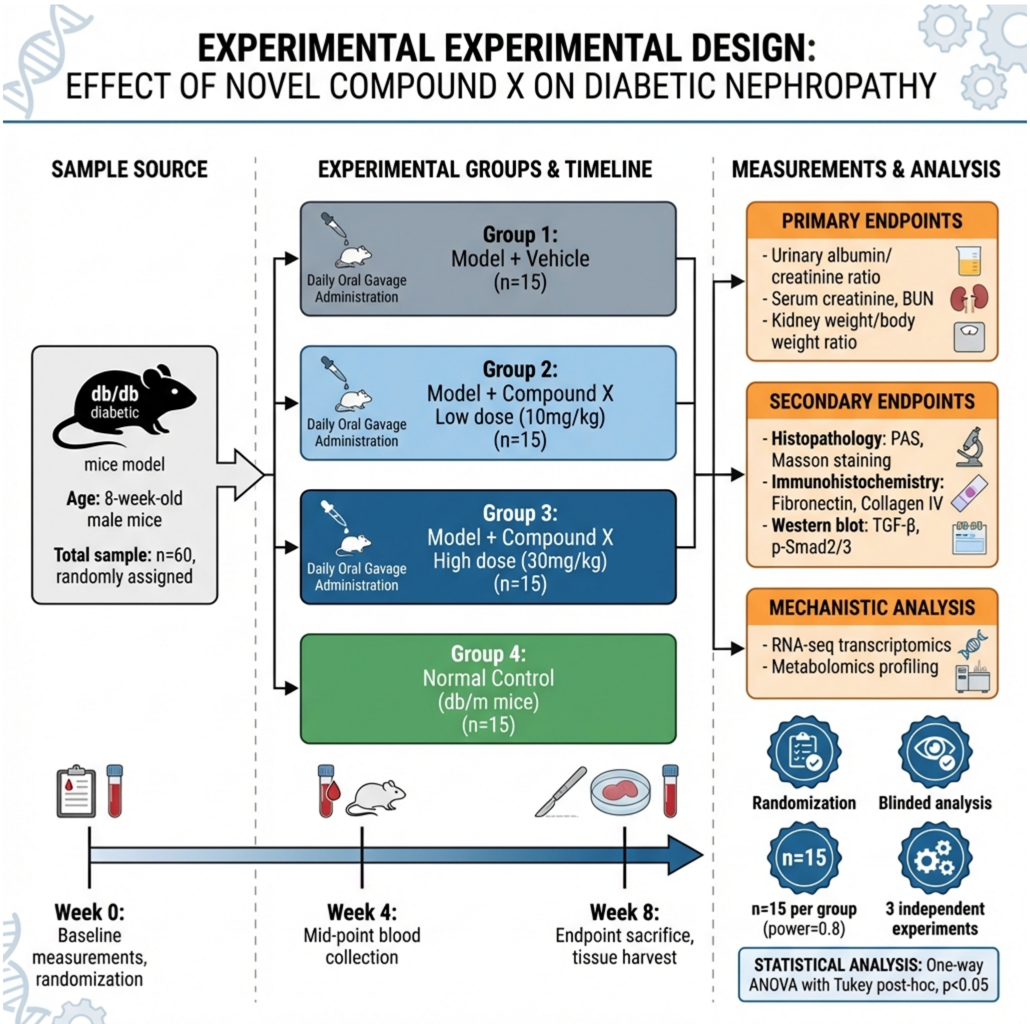

Figure 2: An experimental design diagram depicting a preclinical study with sample source, group allocation, timeline, and measurement endpoints, generated using SciDraw. Source: SciDraw [SciDraw, 2025].

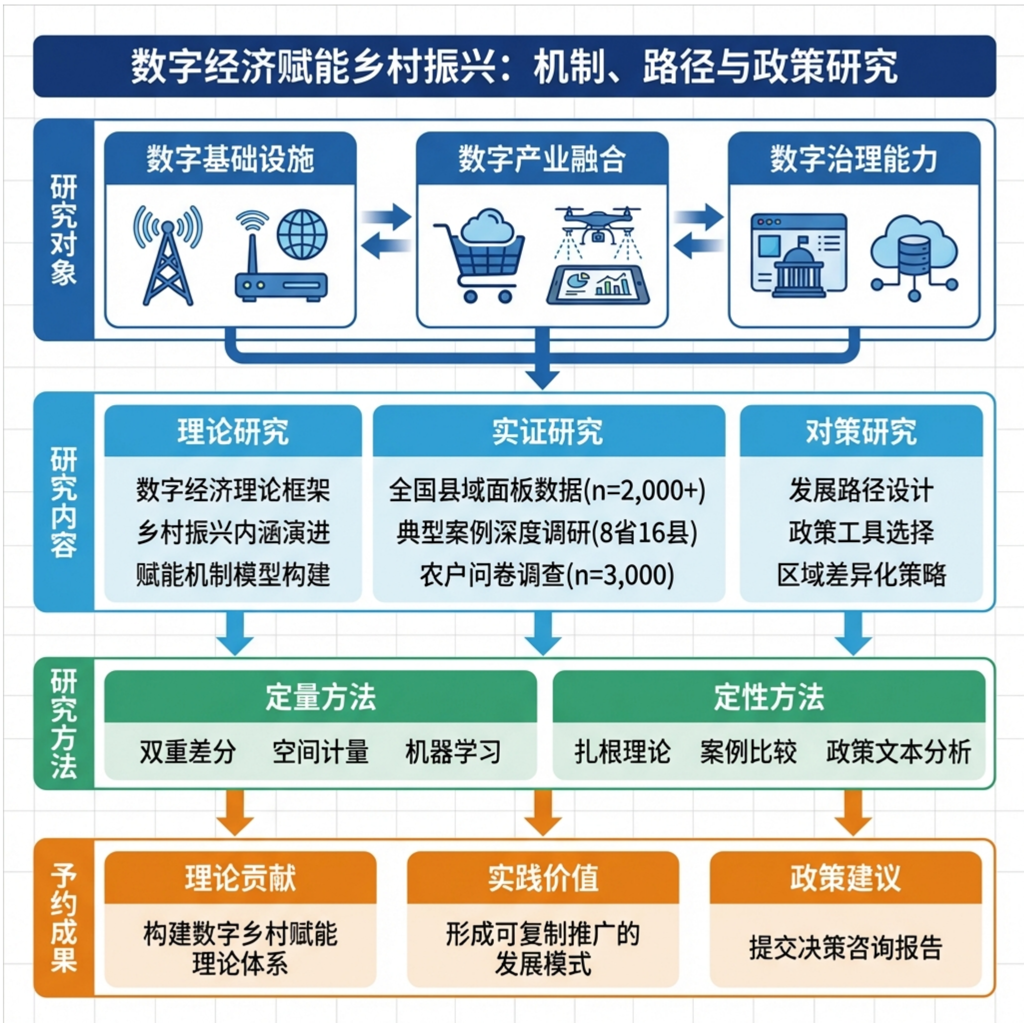

Figure 3: A research framework diagram for a multidisciplinary study on digital economy-enabled rural revitalization, generated using SciDraw. The figure integrates research objectives, methods, and expected outcomes in a structured layout. Source: SciDraw [SciDraw, 2025].

Figure 4: An expected outcomes and impact diagram for a research grant proposal, generated using SciDraw. The concentric ring design organizes outputs from project core to societal impact across temporal scales. Source: SciDraw [SciDraw, 2025].

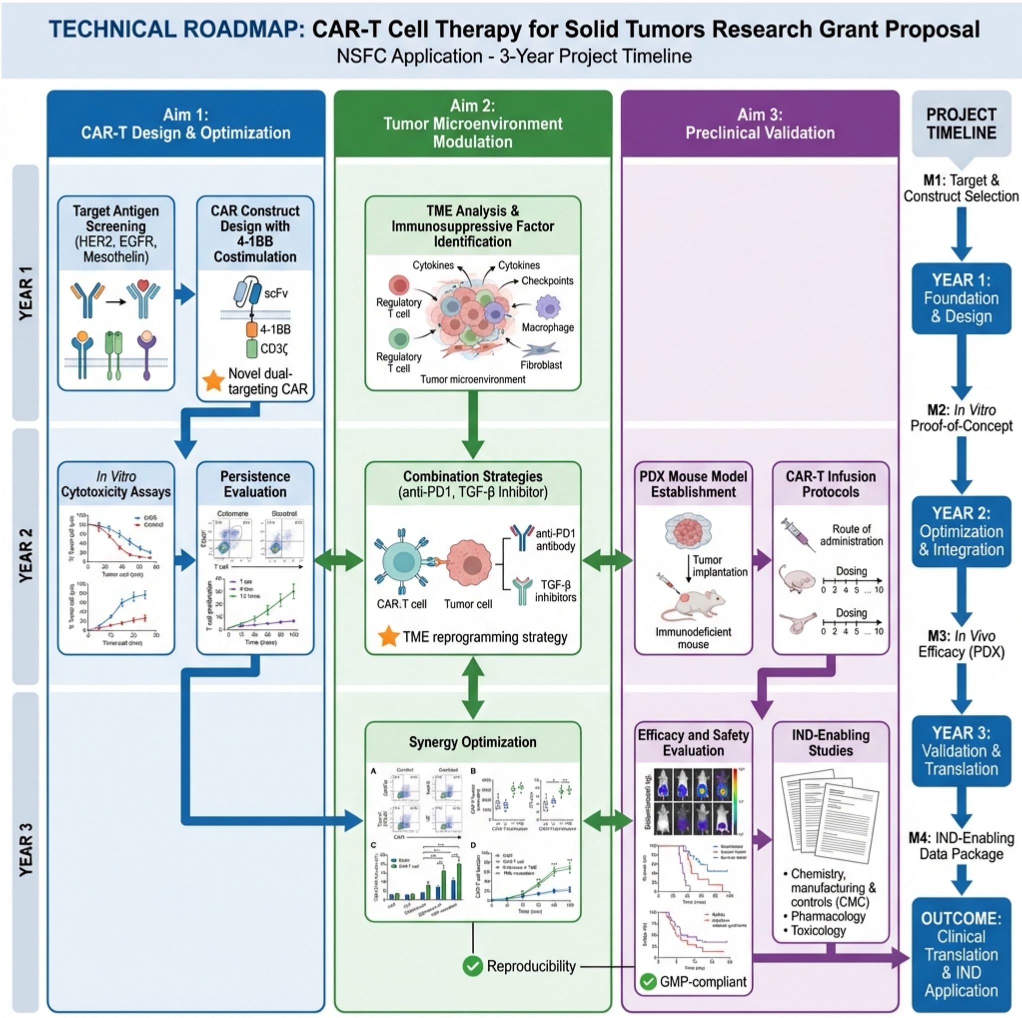

Figure 5: A technical roadmap for a multi-year research program on CAR-T cell therapy for solid tumors, generated using SciDraw. The figure integrates experimental aims, milestones, and project timelines in a structured visual format. Source: SciDraw [SciDraw, 2025].

figure generation:

- Accurate and legible text rendering within complex diagrams;
- Consistent visual style across different figure types;
- Domain-appropriate use of color, iconography, and spatial organization;
- Sufficient detail for inclusion in academic manuscripts without post-editing.

4.4 Selection Criteria for AI Figure Tools

Based on our analysis, we recommend that researchers evaluate AI figure-generation tools using the following criteria:

1. **Output quality:** Does the tool produce figures that meet the visual standards of the target journal?
2. **Domain specificity:** Does the tool understand the conventions of scientific illustration?
3. **Text accuracy:** Can the tool reliably render labels, annotations, and legends?
4. **Reproducibility support:** Does the tool archive generation parameters for disclosure?
5. **Legal clarity:** What are the copyright and licensing terms for generated images?
6. **Iterative workflow:** Can the researcher refine the output through conversation rather than starting from scratch?

5 Proposed Best-Practice Guidelines

Based on our survey of publisher policies (Section 2), analysis of community concerns (Section 3), and comparison of available tools (Section 4), we propose the following best-practice guidelines for researchers using AI-generated figures in academic publications.

5.1 Disclosure Statements

We recommend a standardized three-part disclosure framework:

1. **Methods Section:** Include a dedicated subsection titled "*AI-Assisted Figure Generation*" that specifies:
   - The AI tool(s) used (name, version, and URL);
   - Which specific figures were AI-generated or AI-assisted;
   - A brief description of the generation process (e.g., text-to-image, iterative refinement);
   - The date of generation and, if available, the model version.

2. **Figure Legends:** Each AI-generated figure should include a note in the legend, e.g., "*This figure was generated using [Tool Name] (version X.Y) with iterative prompt refinement. The generation prompt and metadata are available in the Supplementary Materials.*"

3. **Cover Letter:** Briefly mention to the editor that AI tools were used for figure generation and that full disclosure is provided in the manuscript.

Example disclosure statement:

> *Figures 1, 3, and 5 in this manuscript were generated using SciDraw (`https://sci-draw.com`), an AI-powered scientific illustration platform. The figures were created through iterative prompt-based generation and refined through the platform's conversational interface. The full generation prompts and metadata are provided in Supplementary Table S1. All figures were reviewed by the authors for scientific accuracy and visual fidelity.*

5.2 Human Review and Quality Control

AI-generated figures should never be published without careful human review. We recommend the following quality-control checklist:

- **Scientific accuracy:** Do all labels, annotations, and spatial relationships correctly represent the intended science?
- **Visual consistency:** Is the figure consistent with the visual style of other figures in the manuscript?
- **Text legibility:** Are all text elements correctly spelled and legible at print resolution?
- **Data integrity:** If the figure contains any data-derived elements, have these been verified against the source data?
- **Bias check:** Does the figure inadvertently introduce visual biases (e.g., misleading proportions, suggestive color coding)?

5.3 Aligning with Journal Policies

We recommend the following workflow for ensuring compliance with journal-specific policies:

1. **Pre-submission:** Review the target journal's AI policy before figure generation. Identify any categorical restrictions (e.g., Cell Press's prohibition on AI-generated data figures).
2. **During generation:** Use tools that support metadata archiving, such as SciDraw, to facilitate subsequent disclosure.
3. **Pre-submission review:** Have a co-author independently verify all AI-generated figures for accuracy.
4. **Submission:** Include disclosure in the methods section, figure legends, and cover letter as described above.
5. **Post-acceptance:** Ensure that any journal-specific formatting requirements (e.g., resolution, file format) are met. Note that AI-generated figures may require format conversion.

5.4 Record Keeping

For long-term reproducibility, we recommend that researchers:

- Archive the full prompt text and generation parameters for each AI-generated figure;
- Record the model name, version, and platform (e.g., "SciDraw, Gemini 2.5 Flash backend, March 2026");
- Store original output files at maximum resolution;
- Consider depositing generation metadata in a supplementary repository (e.g., Zenodo, Figshare).

6 Conclusion

AI-generated figures represent both an opportunity and a challenge for academic publishing. Our survey reveals that the policy landscape is rapidly evolving but remains fragmented, with significant variation in how publishers approach AI-generated visual content. We identify reproducibility, authorship, misinformation, and copyright as the primary concerns driving current policies.

The practical examples discussed in this paper—generated using SciDraw [SciDraw, 2025] as a domain-specific case study—indicate that current AI tools can produce figures approaching the visual and informational standards of academic publishing, particularly for schematic diagrams, research frameworks, and conceptual illustrations. At the same time, these examples do not by themselves establish superiority over manual workflows or general-purpose tools, nor do they resolve the editorial and legal uncertainties surrounding AI-generated imagery.

We propose a set of best-practice guidelines centered on transparent disclosure, rigorous human review, and systematic record keeping. We believe that widespread adoption of these guidelines can help the academic community realize the benefits of AI-assisted figure generation while maintaining scientific integrity.

This study has several limitations. First, publisher policies continue to evolve, so the policy map reported here should be treated as time-sensitive. Second, our comparison of tools is qualitative rather than experimentally validated. Third, the case studies emphasize communicative and schematic figures; they do not justify the use of AI-generated imagery for primary data presentation. Future work should therefore include longitudinal tracking of editorial policies, controlled usability studies comparing authoring workflows, and standardized reporting templates for AI-assisted figure provenance.

Looking ahead, we call upon publishers to:

- Develop more specific and harmonized guidelines for AI-generated figures;
- Distinguish clearly between AI-generated data figures and AI-generated schematic/conceptual figures;
- Invest in tools and processes for detecting AI-generated content during peer review;
- Engage with the research community to develop evolving best practices.

The future of scientific illustration is likely to be hybrid, combining human expertise with AI capabilities. By establishing clear norms now, the academic community can ensure that this transition enhances, rather than undermines, the reliability and clarity of scientific communication.

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