

Building Open Science into Graduate Training in Clinical Psychology

Jeffrey M. Girard

Department of Psychology, University of Kansas

Author Note

Jeffrey M. Girard  <https://orcid.org/0000-0002-7359-3746>

Supplemental materials are available from: <https://github.com/jmgirard/cps2025>

Correspondence concerning this article should be addressed to Jeffrey M. Girard,
Department of Psychology, University of Kansas, 1415 Jayhawk Blvd (Room 426), Lawrence, KS
66045, USA, Email: jmgirard@ku.edu

Abstract

Open science promises greater transparency and rigor, yet clinical psychology has lagged in integrating it into graduate training. This commentary builds on recent evidence that open-science instruction in U.S. programs remains uneven and largely conceptual. I argue that progress requires more than awareness: it depends on pedagogical scaffolding, computational infrastructure, and cultural alignment. Embedding reproducible, code-based workflows, literate programming, and ethical transparency throughout training can make openness both feasible and normative. By treating transparency as a professional competency, supported by open educational resources and institutional incentives, clinical psychology can model how to cultivate a sustainable culture of open science.

Keywords: commentary, open science, graduate training, research methods

Building Open Science into Graduate Training in Clinical Psychology

Open science offers powerful tools for transparency and rigor, yet clinical psychology has lagged behind other subfields in embedding them in graduate training. Much of this lag reflects distinct headwinds: handling sensitive patient data, coordinating with clinics and IRBs, and studying rare conditions ([Tackett et al., 2017](#)). Still, these factors do not fully explain the gap. Core practices such as preregistration, code sharing, and reproducible workflows can be taught and adopted despite them.

Drawing on syllabus audits and graduate-student surveys, Van Til et al. ([in press](#)) document that open-science training is present in some U.S. programs but uneven overall. Readings and occasional assignments appear, yet hands-on opportunities to practice core behaviors are scarce. Students are generally interested, but many remain unfamiliar with practices such as registered reports.

Writing as a clinical psychologist with a strong computational focus, I take an opinionated stance: open science will not advance through exposure to principles alone. Graduate programs must provide sustained, scaffolded, and hands-on training that turns open-science ideals into routine habits and integrates modern computational tools. Building on Van Til and colleague's findings, I argue that progress depends on three interconnected fronts: pedagogical scaffolding, computational infrastructure, and cultural alignment.

Building Open Science into Graduate Training

If psychology is to prepare the next generation of scientifically rigorous researchers, open-science principles must be woven into the curriculum from the very beginning of graduate education. The first semester plays a disproportionate role in shaping a student's identity as a researcher ([Bruss & Kopala, 1993](#); [Cruess et al., 2015](#)). Early coursework in methods and statistics not only teaches design and analysis but also transmits the norms that define what counts as rigorous and responsible science. Programs that postpone or marginalize open-science instruction implicitly signal that transparency is peripheral rather than central to good research practice.

An effective approach should scaffold open-science training across the full arc of graduate

development. Introductory methods courses can present the rationale for transparency and provide structured preregistration exercises that help students distinguish between exploratory and confirmatory inquiry. Early statistics courses can pair reproducible code with transparent documentation, allowing students to practice the full cycle of analysis, interpretation, and reporting. As students progress, they should apply these skills to projects grounded in their own interests: designing a study, preregistering hypotheses, analyzing original data, and depositing materials in an open repository. By the dissertation stage, students ought to be fluent in core open-research workflows such as preregistration, code and data sharing, and reproducible reporting, while optionally experimenting with registered reports, replication studies, or version-controlled collaboration.

Because many graduate programs teach methods and statistics across subfields (not just within clinical psychology; [Aiken et al., 2008](#)), instructors can collaborate with content-area faculty to ensure students apply open-science tools (e.g., preregistration, reproducible code, transparent reporting) to problems that are relevant to their specific domains. Once students have developed core competencies, instructors can assign occasional exercises using parallel prompts or datasets from different areas (e.g., clinical, social, developmental), all evaluated using shared criteria. To further support transfer across domains, instructors can introduce low-effort connectors such as brief guest visits, interdisciplinary panels, or mini-modules that demonstrate how workflows generalize across fields. This coordinated approach makes open-science practices feel relevant and inclusive without requiring new courses or major scheduling changes.

Adoption also depends on open educational resources (OER) that lower preparation costs and standardize quality. Reusable, creative-commons-licensed syllabi, textbooks, assignment templates (e.g., preregistration exercises, case-based lab reports), exemplar repositories with de-identified or synthetic data, and instructor guides can make it far easier for time-limited faculty to integrate open-science content ([Mondal, 2025](#); [Wiley et al., 2014](#)). Scientific organizations and disciplinary societies are well positioned to underwrite and curate these materials (e.g., competitive micro-grants for OER development, peer-reviewed teaching portals, or “starter kits”

aligned to accreditation competencies). Department-level incentives (e.g., recognizing OER creation as scholarly contribution, providing small teaching fellowships for graduate assistants to localize materials) further increase the odds of durable adoption.

Of course, this scaffolding must be realistic about the demands on both students and faculty. First-year students already face heavy demands in learning statistics, research design, and clinical work. Adding open-science expectations without sufficient structure risks overwhelming rather than empowering them. Likewise, many instructors support transparency in principle but lack the time, training, or institutional backing to redesign courses and assignments. Addressing these challenges means providing pedagogical supports, not lowering expectations: template-based preregistrations, staged code assignments, workshops on advanced topics, and faculty development resources that make curricular change feasible.

Departments can further reduce barriers by offering quick-start guides for OSF/Git/GitHub, curated repositories of reusable assignments, and short peer-teaching circles or office hours where faculty troubleshoot together. Naming an “open-science lead” (or small working group) to coordinate resources, host demos, and maintain internal documentation helps normalize transparency as shared, sustainable practice.

Small, tangible incentives also matter—micro-grants, summer stipends, targeted TA support, or one-time course releases for substantial redesigns—paired with recognition of OER and reproducible teaching artifacts in annual reviews and promotion criteria. In short, scaffolding must apply not only to students’ learning but to instructors’ adoption of new practices. Embedding transparency in graduate education therefore depends on both sound pedagogy and the technical infrastructure that makes open practices practical and valued.

Tools and Workflows that Empower Transparency

Open science is grounded in values and policies, but it is sustained by tools and technologies that make those values actionable. The tools students learn early on often become the scaffolding for their scientific careers; ensuring they support reproducibility, transparency, and collaboration is therefore essential.

Code-Based Workflows

Perhaps the most transformative shift in recent research practice has been the move from costly, point-and-click statistical software to open-source, code-based workflows. Whether students use R, Python, or another programming language, writing and documenting analytic scripts fosters a level of transparency and reproducibility that manual workflows cannot match. Analyses encoded in readable, versioned scripts can be reviewed, rerun, and built upon by others. The analysis itself becomes an object of scientific discourse, not a black box (Sandve et al., 2013).

Some point-and-click tools can export “syntax” or logs of the steps taken. This is better than nothing and can aid transparency, but exported syntax is often incomplete, hard to reuse, and brittle across software versions. In contrast, fully code-based workflows produce clear, shareable scripts that plug into later practices we describe (e.g., keeping a clean history of changes and packaging the computational environment) making verification, collaboration, and long-term reuse more reliable.

There is no justifiable scientific reason to withhold analytic code from a published study. While data may need protection (e.g., for legal or ethical reasons), code is part of the method. Yet many students are never taught to view code as a scientific product. This gap represents a clear target for curricular reform.

Literate Programming

Literate programming treats code and narrative text as equally important parts of scientific communication. Tools like Quarto, an open-source publishing system, allow researchers to seamlessly combine text, code, and output (figures, tables, diagnostics) in one document (Scheidegger et al., 2025). Quarto supports citations, equations, and cross-references, producing reports, slides, websites, or manuscripts that are fully reproducible.¹

In graduate courses, literate programming encourages students to document their reasoning, explain decisions, and produce reports that can be rerun at any time. This approach is ideal for methods assignments, replication projects, and theses. It also reflects how high-quality

¹ This article was created using Quarto. See github.com/jmgirard/cps2025 for the code.

research is increasingly disseminated—not just through manuscripts but through richly documented supplemental materials that promote transparency and cumulative science. These same practices prepare students to collaborate on interdisciplinary research teams and open doors to roles beyond academia, including in data science and applied research, where reproducible workflows are essential.

Beyond the Basics

While more advanced, two computational frameworks further enhance transparency and reproducibility. **Version control** helps you keep a running history of your work so you can see what changed, undo mistakes, and work with others without overwriting each other. Today, Git is the standard tool for version control, and services like GitHub and GitLab make it easy to store projects online (either publicly or privately) and to share them with collaborators ([Bryan, 2016](#); [Chacon & Straub, 2014](#)). Using version control builds accountability and clarity: anyone can trace what was done and when. As a practical student project, publishing a basic researcher website built with Quarto and hosted for free on GitHub introduces versioned, public-facing scholarship in a low-stakes, hands-on way.

Environment management aims to make the same code run the same way anywhere by reproducing the software environment (i.e., operating system, system libraries, programming-language version, and packages). Tools like R's *renv* and Python's *virtualenv* record and restore the exact package versions used and, for even more reliability, other tools can create a self-contained copy of the entire environment. For R users, *rang* ([Chan & Schoch, 2023](#)) makes it straightforward to build such copies with Docker ([Merkel, 2014](#)), locking the operating system, R version, and packages to known snapshots. Packaging the environment with the project (e.g., alongside a manuscript or preregistration) makes complex work easier to share, rerun, and verify years later, strengthening replication and extension.

Though more technical, these methods future-proof scientific work and are increasingly vital for interdisciplinary and collaborative projects.

Tools as Values in Action

These tools do more than ensure technical accuracy—they teach a way of thinking. Code-based workflows, literature programming, and environment management foster habits of documentation, foresight, and humility (Table 1). They signal that science is not only about reaching results but about making the process intelligible and reviewable. By teaching these tools explicitly and modeling their use, programs can help students build workflows that are not only reproducible but also resilient and collaborative. In a world where scientific claims face growing scrutiny, these capacities are not optional; they are part of what it means to do science well.

Beyond technical robustness, open tools reduce inequities in access to knowledge. Open-source languages, shared teaching resources, and transparent workflows allow smaller or underfunded programs to match the standards of well-resourced institutions. By emphasizing openness as both a scientific and an equity value, graduate training can broaden who participates in and benefits from psychological science.

These same values extend beyond the classroom and into publication. Journals and editors occupy a powerful position in normalizing open-science workflows. When submission systems reward transparency (e.g., through preregistration badges, open-data links, or replication features), they reinforce the habits cultivated in training. Aligning incentives across education and publication ensures that the same principles guiding data collection and analysis also guide dissemination and recognition.

Yet even the best tools cannot overcome the ethical, institutional, and cultural barriers that shape how openness is practiced. These realities are particularly salient in clinical psychology.

Ethical and Institutional Realities in Clinical Training

Clinical psychology occupies a distinctive position at the intersection of scientific training and professional regulation. Because most programs operate under formal accreditation standards, accrediting bodies such as the American Psychological Association (APA) and the Psychological Clinical Science Accreditation System (PCSAS) exert substantial influence over curricular priorities. Depending on how they define competencies in research and ethics, these organizations

can either facilitate or hinder the adoption of open-science practices. Clinical psychology thus functions as a model-setting domain for embedding transparency within professional education, where accreditation requirements, competency benchmarks, and supervisory structures can translate principles into enforceable expectations.

At the same time, clinical training entails challenges few other areas face ([Tackett et al., 2017](#)). Ethical and legal imperatives of patient confidentiality complicate sharing of raw data, preregistration of sensitive protocols, and replication of clinical trials (e.g., [Ness, 2007](#)). Research partnerships with hospitals, clinics, and community agencies are governed by data-use agreements that may limit dissemination. Students must also balance research with coursework and intensive clinical practica, leaving limited bandwidth to master new computational tools. These constraints can make open-science ideals seem aspirational rather than achievable.

Yet the very features that complicate openness also create opportunities for innovation. Clinical psychology can pioneer frameworks for *ethical transparency* that balance rigor with privacy. Examples include using de-identified or synthetic datasets for teaching, secure data enclaves for authorized replication, and preregistration formats that allow embargoes until sensitive work concludes (e.g., [Howison et al., 2024](#); [Liu et al., 2025](#)). Because clinical training already integrates ethics and reflective supervision, open-science competencies can be framed as extensions of professional responsibility rather than external mandates. Linking transparency to ethical conduct reinforces its relevance to both science and care.

Even with these structures in place, real research is messy. Students learning statistics may lack the knowledge to preregister analyses in full detail, and projects often evolve in response to data patterns or reviewer feedback ([Nosek et al., 2019](#); [Simmons et al., 2021](#)). Rigid preregistration can backfire if it fosters box-checking over critical reflection. Instead, students should be taught to view preregistration as a flexible tool for clarifying thought, not constraining it: distinguishing exploratory from confirmatory work, documenting changes transparently, and recognizing that deviation is part of learning. Similarly, registered reports should be seen not as universal solutions but as gold standards for certain kinds of confirmatory research.

Another subtle barrier is the culture of perfectionism that pervades many graduate programs. When open science is framed in idealized terms, students may equate rigor with flawlessness and transparency with self-exposure. For trainees already navigating imposter syndrome, this can breed paralysis rather than curiosity. Faculty (in both teaching and research roles) can counter this by modeling vulnerability—sharing imperfect code, troubleshooting errors in front of students, and emphasizing that open science is about clarity, not perfection ([Strand, 2025](#)).

Finally, not everyone shares the same values or priorities that motivate open-science advocacy (e.g., [Bazzoli, 2022](#)). While many view transparency as central to integrity, others prioritize innovation, idiographic understanding, or public health impact. Some are skeptical that preregistration and data sharing improves understanding; others worry these practices might disadvantage those working with limited resources or delay progress on publishable work. These differences reflect genuine pluralism in what scientists see as the purpose of research. Because clinical psychology operates at the nexus of scientific and professional ethics, conversations about open science must engage (rather than override) this diversity of commitments. Promoting openness, therefore, is as much a cultural project as a technical or pedagogical one. It requires empathy, dialogue, and respect for principled disagreement.

Conclusion

Van Til and colleagues have provided a valuable service by empirically documenting what many open-science advocates in clinical psychology have long suspected: while interest in transparency and rigor is growing, graduate training has yet to catch up. Their registered report offers both a clear-eyed assessment of the current state and a hopeful reminder that students are eager to engage when given the opportunity.

But awareness is only the first step. For open science to take root in clinical psychology, programs must invest in the pedagogy, infrastructure, and culture that make transparency not just possible, but normative. That means treating reproducibility as a core competency, integrating code-based workflows and preregistration early in the curriculum, supporting faculty with

resources and time, and acknowledging that transparency will look different across projects. Imperfection is not a flaw but a feature of honest science.

At the same time, accrediting bodies, journals, and funders can align incentives by treating transparency as evidence of rigor and rewarding the labor that sustains it. Graduate students themselves can be catalysts for change through peer-learning groups and shared repositories. Open science thus becomes a collective practice, not a solitary ideal—sustained by aligned structures, supportive mentorship, and everyday habits of openness. Clinical psychology, with its dual commitment to ethics and evidence, is uniquely positioned to lead this cultural transformation.

Open science is a practice we choose, repeatedly, in the face of complexity and constraint. It is a commitment to make our work intelligible to others and accountable to the communities we serve. For clinical psychological science, that commitment is essential—and so is the work of teaching it. A sustainable culture of open science begins in the classroom, is reinforced through mentorship, and is sustained by institutions that value good science not only for its outcomes but for its openness in process.

Acknowledgments

This manuscript was written with the assistance of a large language model. The author has independently verified the accuracy, validity, and appropriateness of all substantive content.

Author Contributions

Conceptualization: J. Girard; Writing – Original Draft Preparation: J. Girard.

Conflicts of Interest

The author declares that there were no conflicts of interest with respect to the authorship or the publication of this article.

References

Aiken, L. S., West, S. G., & Millsap, R. E. (2008). Doctoral training in statistics, measurement, and methodology in psychology: Replication and extension of Aiken, West, Sechrest, and Reno's (1990) survey of PhD programs in North America. *American Psychologist*, 63(1),

32–50.

- Bazzoli, A. (2022). Open science and epistemic pluralism: A tale of many perils and some opportunities. *Industrial and Organizational Psychology*, 15(4), 525–528.
- Bruss, K. V., & Kopala, M. (1993). Graduate school training in psychology: Its impact upon the development of professional identity. *Psychotherapy: Theory, Research, Practice, Training*, 30(4), 685–691.
- Bryan, J. (2016). *Happy Git and GitHub for the useR*. <https://happygitwithr.com/>
- Chacon, S., & Straub, B. (2014). *Pro Git* (2nd ed.). Apress.
- Chan, C., & Schoch, D. (2023). Rang: Reconstructing reproducible R computational environments. *PLOS ONE*, 18(6), e0286761.
- Cruess, R. L., Cruess, S. R., Boudreau, J. D., Snell, L., & Steinert, Y. (2015). A schematic representation of the professional identity formation and socialization of medical students and residents: A guide for medical educators. *Academic Medicine*, 90(6), 718.
- Howison, M., Angell, M., & Hastings, J. S. (2024). Protecting sensitive data with secure data enclaves. *Digital Government: Research and Practice*, 5(2), 1–11.
- Liu, Q., Shakya, R., Jovanovic, J., Khalil, M., & de la Hoz-Ruiz, J. (2025). Ensuring privacy through synthetic data generation in education. *British Journal of Educational Technology*, 56(3), 1053–1073.
- Merkel, D. (2014). Docker: Lightweight linux containers for consistent development and deployment. *Linux Journal*, 2014(239), 2.
- Mondal, H. (2025). Copyright and creative commons licenses in scholarly publishing: A practical guide for researchers. *Journal of Clinical Imaging Science*, 15, 32.
- Ness, R. B. (2007). Influence of the HIPAA privacy rule on health research. *JAMA*, 298(18), 2164–2170.
- Nosek, B. A., Beck, E. D., Campbell, L., Flake, J. K., Hardwicke, T. E., Mellor, D. T., van 't Veer, A. E., & Vazire, S. (2019). Preregistration is hard, and worthwhile. *Trends in Cognitive Sciences*, 23(10), 815–818.

- Sandve, G. K., Nekrutenko, A., Taylor, J., & Hovig, E. (2013). Ten simple rules for reproducible computational research. *PLOS Computational Biology*, 9(10), e1003285.
- Scheidegger, C., Woodhull, G., Dervieux, C., Teague, C., Allaire, J. J., & Xie, Y. (2025). *Quarto*. Posit, PBC. <https://quarto.org>
- Simmons, J. P., Nelson, L. D., & Simonsohn, U. (2021). Pre-registration is a game changer. But, like random assignment, it is neither necessary nor sufficient for credible science. *Journal of Consumer Psychology*, 31(1), 177–180.
- Strand, J. F. (2025). Error tight: Exercises for lab groups to prevent research mistakes. *Psychological Methods*, 30(2), 416–424.
- Tackett, J. L., Lilienfeld, S. O., Patrick, C. J., Johnson, S. L., Krueger, R. F., Miller, J. D., Olmanns, T. F., & Shrout, P. E. (2017). It's time to broaden the replicability conversation: Thoughts for and from clinical psychological science. *Perspectives on Psychological Science*, 12(5), 742–756.
- Van Til, K., Phillips, N., Du, T., Rose, L., Miller, J., & Lynam, D. (in press). Open science training in APA-accredited clinical psychology programs: A registered report. *Clinical Psychological Science*.
- Wickham, H., Çetinkaya-Rundel, M., & Golemund, G. (2023). *R for Data Science* (2nd ed.). O'Reilly Media. <https://r4ds.hadley.nz/>
- Wiley, D., Bliss, T. J., & McEwen, M. (2014). Open educational resources: A review of the literature. In J. M. Spector, M. D. Merrill, J. Elen, & M. J. Bishop (Eds.), *Handbook of research on educational communications and technology* (pp. 781–789). Springer.

Table 1*Recommended Tools and Readings*

Topic	Tool	Reading
Code-based workflows	tidyverse	Wickham et al. (2023)
Literate programming	Quarto	Scheidegger et al. (2025)
Version control	Git	Bryan (2016)
Environment management	rang	Chan and Schoch (2023)