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Toward open science in marketing research

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ABSTRACT

The open science paradigm has gained prominence in marketing as researchers seek to enhance the validity, reliability, and transparency of research methods and findings. Journals and institutions increasingly encourage or require open science practices, and many authors have started to adapt to and meet these new research and publishing expectations. We provide guidance for effectively implementing open science practices in empirical marketing research. Our recommendations, are tailored to the unique methodological approaches and challenges of each subdiscipline and their specific research contexts. Successful integration of these practices into academic marketing research will require concerted and collaborative efforts among authors, journals, institutions, and funding agencies. We argue that the gradual, thoughtful adoption of these principles and practices will improve the quality and efficiency of scientific discovery.

1. Introduction

Over the past decade, scholars in marketing have faced increasing demands for greater validity, reliability, and transparency in their research methods and findings. In response to these new demands, a growing number of marketing researchers, publishers, and institutions are embracing and implementing open science practices and requirements. Open science advocates that "scientific knowledge of all kinds, where appropriate, should be openly accessible, transparent, rigorous, reproducible, replicable, accumulative, and inclusive" (Parsons et al. 2022, p.314).[1] The open science paradigm is actively reshaping academic norms and disrupting traditional research practices. It promises increased rigor and accessibility but also introduces new challenges and demands significant changes in how academic research is conducted.

The open science paradigm gained greater prominence in response to several challenges identified in academic marketing research. The perceived lack of transparency in research practices has raised concerns about a variety of issues, including selective reporting (Simmons & Simonsohn, 2017), *p*-hacking (Head et al. 2015; Brodeur et al., 2016), undisclosed flexibility

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[1] Concepts related to open science, long debated across disciplines, include open access to scientific information (Esanu and Uhlir, 2003), balancing intellectual property rights with open access, industry-academic partnerships, commercialization of discoveries, and researcher compensation (Thursby & Thursby, 2003; Kilger & Bartenbach, 2002). The tension between public funding and universities profiting from patenting faculty research is also a critical issue (Marshall, 2003). While relevant, these topics fall outside the scope of this manuscript.

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in data collection and analytic decisions (Simmons et al., 2011), and insufficient methodological transparency (Berman & Van den Bulte, 2022; Fountain et al., 2023). These practices contribute to publication bias, where studies with novel and positive results are more likely to be published. At the same time, null or negative findings often remain unpublished—distorting the scientific record and biasing evidence-based decision-making—a challenge known as the file drawer problem (Franco et al., 2014; Harrison et al., 2017; Stanley, 2005). In addition, reports of low reproducibility of academic findings in psychology have raised significant doubts about the reliability of published results (Baker, 2016; Nosek et al. 2022; Open Science Collaboration, 2015).

To address these issues, a range of open science practices have been suggested to make the research process more transparent, and the research outputs more accessible and reproducible. These practices include preregistration of research design and analyses, sharing a research project's data, code, and protocols, open access publication, open peer review, open-source software, and greater efforts to disseminate research output and promote collaboration (Crüwell et al., 2019; Parsons et al., 2022). Leading marketing journals have responded to concerns about research reproducibility and research integrity by adopting and encouraging some of these practices (see Appendix Table A1). For example, the *Journal of Marketing Research* requires authors to submit replication packages—including original materials, data, and code—to the editorial staff. The *Journal of Marketing* and *Management Science*, in addition to accepting replication packages, have appointed data editors to review submissions and ensure consistency with the results reported in the manuscript. The *International Journal of Research in Marketing*, *Journal of Consumer Research*, and *Journal of Consumer Psychology* encourage preregistration without requiring it. Similar trends have emerged in economics and psychology, where journals have implemented open science practices such as mandatory data sharing, preregistration, and the publication of replication studies (e.g., Ankel-Peters et al. 2024; Miguel 2021; Vazire, 2018).

The adoption of open science tools in marketing scholarship has been uneven across researchers, journals, and institutions, leading to varying levels of engagement and knowledge. As journals begin implementing new policies requiring open science practices as part of a submission, many scholars are still learning how to use the open science toolkit effectively or remain uncertain about how to manage the multitude of open science tools, demands, and guidelines in their research projects.

To address this concern, this paper focuses on concrete steps for implementing open science practices in empirical marketing research (e.g., quantitative, behavioral, and strategy). We structure our discussion and highlight relevant open science practices across three main stages of an academic research project, emphasizing that each practice needs to be carefully considered and evaluated for its relevance and feasibility within each marketing subfield, research domain, and specific research project[2]:

(1) **planning**, including preregistration, pre-analysis planning, and registered reports, i.e., practices more commonly associated with experimental work in psychology and consumer behavior that may be relevant to some quantitative and strategy marketing research;
(2) **documentation**, with an emphasis on documenting materials, data, and code, a practice highly relevant to quantitative and qualitative work in all research domains; and
(3) **dissemination**, covering the circulation of manuscripts before journal acceptance, engaging in open-access publishing and communicating to broader audiences; a practice all subfields can adopt.

The remainder of the paper proceeds as follows. Section 2 outlines the three stages of research and respective open science practices. Section 3 is intended to help researchers new to open science tools to get started by illustrating the core notions of each practice in the context of three exemplary marketing research projects. Section 4 details how researchers, journals, and institutions can adopt and support applications of the open science toolkit. Section 5 discusses the need to shift towards a more open research culture in marketing academia. Section 6 provides a concluding discussion.

2. Open science practices for marketing research

The open science paradigm emphasizes transparency, reproducibility, and building on accumulated knowledge. Although numerous practices comprise the open science toolkit, we highlight some that may be particularly applicable at the three main stages of the marketing research process: planning, documentation, and dissemination (Fig. 1).

2.1. Planning

A central aspect of open science is transparent and comprehensive planning of the research process, deciding on key features of a research study before it is conducted. Practices that facilitate the separation of pre-planned from data-driven analyses are preregistrations and registered reports (Nosek et al., 2018).

In a *preregistration*, authors document main design elements (e.g., hypotheses and methods decisions, pre-analysis plans) in a dedicated document that is uploaded to a public platform before data collection (e.g., the Open Science Framework, OSF,

[2] For detailed discussions on the opportunities and challenges of open science, see Bahlai et al. (2019), Esanu and Uhlir (2003), Guzzo et al. (2022), Korbmacher et al. (2023), and Munafò et al. (2017).

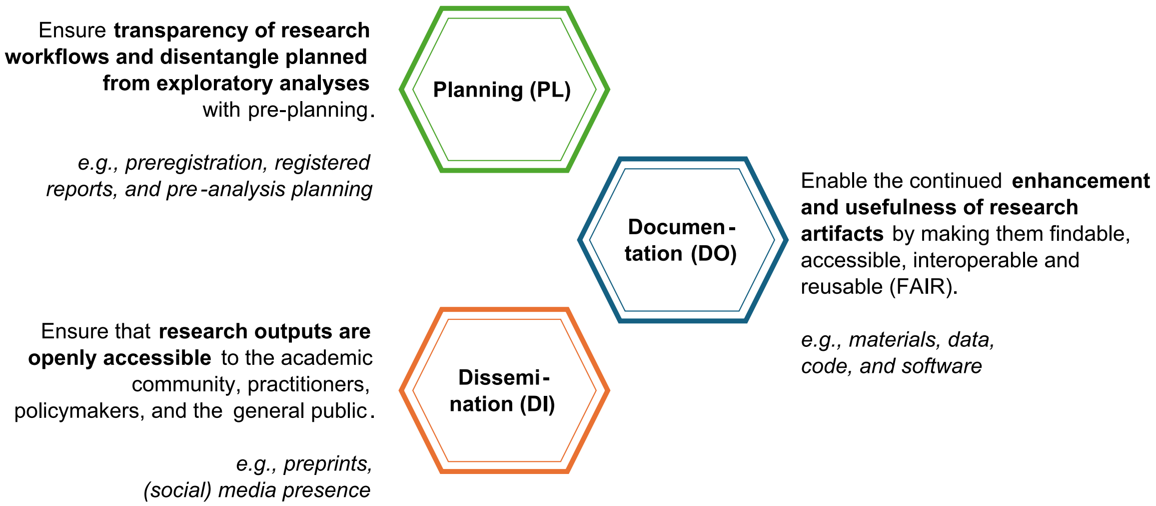


Fig. 1. Open science practices for marketing research. Notes. We depict the three stages of a research project and the corresponding open science practices: (1) planning of a study before it is conducted, (2) documentation of data collection and analysis, and (3) dissemination of research results.

https://osf.io/registries; AsPredicted, https://www.aspredicted.org). Preregistrations can be embargoed, meaning they are non-public for a specified duration. When data collection and analyses are complete, the manuscript submission includes an anonymized version of the preregistration. This preregistration document makes researchers' degrees of freedom and deviations between initial and final data collection and analysis strategies transparent (Simmons et al., 2021). After data collection and analysis, researchers outline deviations from their preregistration in a separate document, including changes requested by reviewers during the publication process. Readers, in turn, can assess the study's findings in light of any deviations from the preregistration. With preregistration, the researcher seeks to ensure transparency of the original research plans, enhancing the credibility of the findings.

A *registered report* is a publication format that involves a two-stage review process (Arpinon and Espinosa, 2023; Chambers and Tzavella, 2022). Specifically, researchers submit a stage one manuscript to a journal that contains all elements of the final manuscript (i.e., research question(s), theoretical framework, proposed hypotheses, methods, and analysis plans) before data are collected. Given a favorable peer review, editors then can issue an in-principle acceptance, with a guaranteed publication conditional on authors carrying out their original plan, regardless of the results. The *International Journal of Research in Marketing* (Pauwels et al. 2024), the *Journal of Consumer Research*, and *Psychology & Marketing,* for example, offer authors the option to submit registered reports.

2.2. Documentation

Open science entails making research artifacts such as materials, data, code, and software openly available in a format that effectively enables their reuse. Open documentation facilitates reproducibility (Rouder, 2016) and allows others to replicate studies and extend research findings (Baker et al., 2023).

Providing reusable materials, data, and code reduces the number of research artifacts that are used only once for one publication and then discarded. Making the best use of available resources is relevant for rich and unique data collected in, for example, quantitative and qualitative field studies. Publishing data sets that require considerable time to collect may be an effective way to facilitate follow-up research. *Marketing Science*, for example, offers an option to do so (Bradlow, 2008). While sharing data and code is crucial to documenting scientific research, sharing other materials (e.g., questionnaires, stimulus materials, experimental scripts) also facilitates follow-up research. For example, sharing materials such as survey scales facilitates standardized construct measurements and reliance on established measures (Elson et al., 2023).

2.3. Dissemination

Marketing researchers can participate in open dissemination and early-stage discussions of their findings. Active engagement within the academic community and with the general public can increase the visibility of research findings. Disseminating findings among academic audiences includes posting preprints and open-access publications (Pennington, 2023). Preprints are early-stage, non-peer-reviewed manuscripts that authors upload to preprint servers. They accelerate scientific discussions by enabling the pre-publication review and use of findings (Moshontz et al., 2021). Unlike preprints (which are, by definition, openly available), many journals and publishers demand fees for open-access publications (i.e., article processing charges, APCs).

Meaningfully reaching a non-academic audience—such as practitioners or policymakers—requires appropriate communication channels to disseminate scientific knowledge (Stäbler and Haenlein, 2024). Importantly, the open dissemination principle closely aligns with the core mission of academia, including business schools—to create and share knowledge in a way that will positively impact organizations and society.

3. Toolkit for implementing open science

Open science practices can be applied to a wide range of marketing research projects, from theory testing to descriptive or predictive studies. To guide researchers in implementing open science practices in specific projects, we illustrate how they can be applied across three exemplary research projects (see Fig. 2).

Project 1 focuses on theory testing through a lab experiment, a common setting in consumer behavior research. In this project, the authors could, for example, test how information display affects product choice. To increase research transparency, the authors in this hypothetical project decide to preregister their experimentation protocols, data collection procedures, and hypotheses. In addition, they provide all materials, data, and code openly.

Project 2 is an exploratory study based on archival scanner panel data and consumer surveys. Exploratory studies, often used in strategy and quantitative marketing research, may investigate, for example, how sustainability labels impact food purchase decisions, or the role of loyalty programs in consumer choice. Given the complex data preparation (e.g., with many source files), the potential need for data-driven refinement of measurements (e.g., rolling means with different window lengths), and econometric modeling (e.g., use of instrumental variables), the authors decide to prepare detailed documentation to enhance transparency and reproducibility. However, while the authors may use preregistration to outline general research objectives and variables, they do not pre-commit to specific hypotheses.

Project 3 is a quantitative marketing study with a predictive focus. Such projects might include predicting customer acquisition and retention via email marketing or product returns based on information in a web shop. The primary goal is to develop effective predictions rather than test specific theories. Preplanning would not be emphasized since the aim is not to make definitive theoretical claims. Instead, the focus is on comprehensive documentation of data sources, data management procedures, and analysis techniques to ensure transparency and reproducibility of the models used.

3.1. Planning

Researchers can improve their planning before data collection. An easy way to get started is by conducting a preregistration, as depicted in Fig. 3.

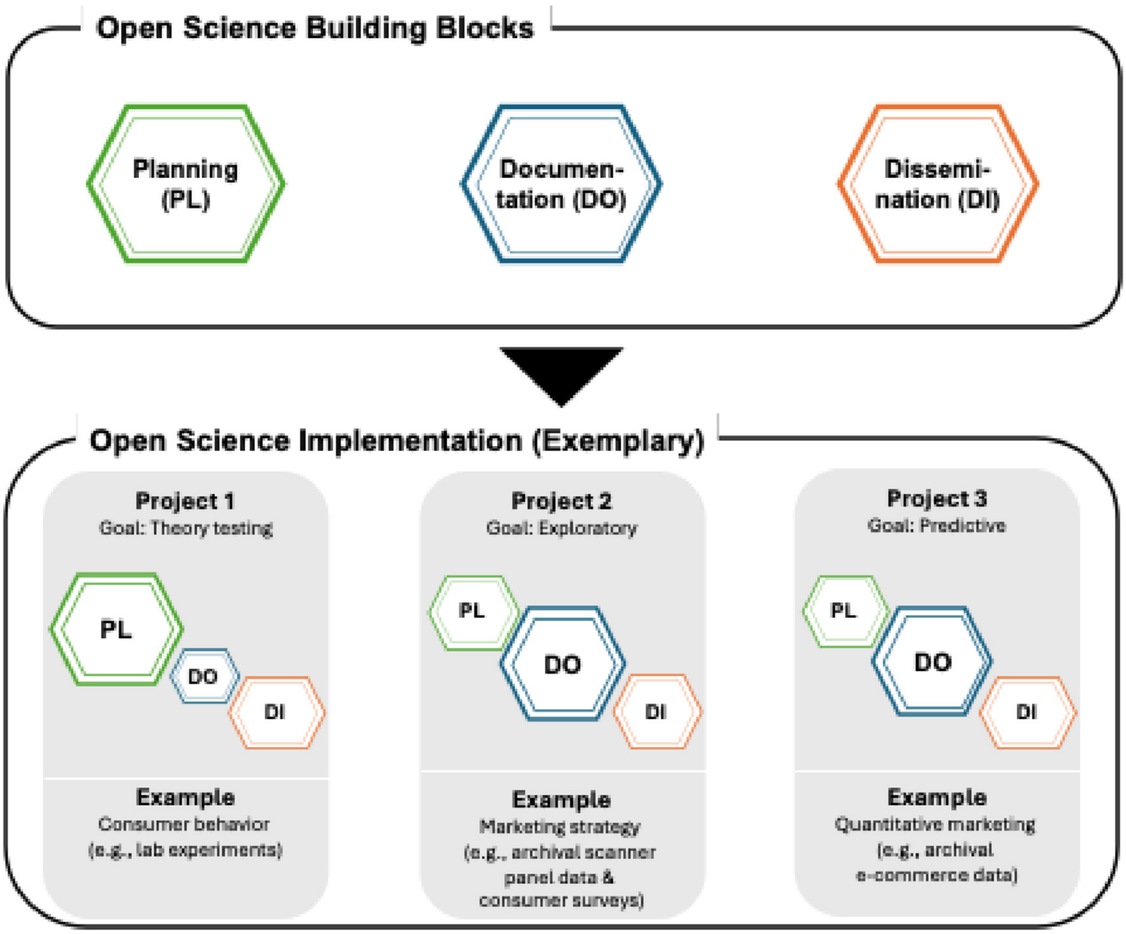
Preregistrations can take various forms. One option is to use existing templates (e.g., the *AsPredicted* template, which contains eight basic questions for confirmatory research). Specialized templates exist for exploratory approaches, qualitative data, and secondary data analyses to plan without specifying all methodological and data processing decisions (see Appendix Table A2 for an overview of preregistration templates).

Researchers then fill in the preregistration template. Preregistrations can include the research hypotheses, sampling procedure, sample size, research design, testing conditions, stimuli, measures, outcome variables, data coding and aggregation method, criteria for data exclusions, and statistical analyses, including potential variations of those analyses (Hardwicke and Wagenmakers, 2023). Further data analytical elements can be specified including, for example, how a hold-out sample will be used, which model evaluation criteria will be considered (Shmueli, 2010) or which analytical stance will be taken in a qualitative analysis (Gehman et al., 2018). In the next step, researchers submit the preregistration document to a dedicated platform (e.g., OSF: https://osf.io/registries; AsPredicted: https://www.aspredicted.org), and set—if desired—an embargo period before the preregistration becomes public.

Creating a preregistration for a consumer behavior experiment, as outlined in Project 1, involves clearly defining the research questions and hypotheses to be tested, specifying the main variables, detailing the sampling and data analysis plan, and briefly outlining planned secondary analyses and robustness checks. The design of many consumer behavior experiments follows a predefined procedure and has a foreseeable data structure, meaning that the information contained in preregistration can be quite detailed.

However, requiring a detailed preregistration with a complete pre-analysis plan in exploratory or predictive projects such as Projects 2 and 3 can result in many deviations from the preregistration. Therefore, detailed pre-planning may be impractical in certain research settings, such as inductive studies that start with empirical observations to identify patterns and develop theories (Golder et al., 2023), or qualitative research, where flexible adaptation in data collection is often necessary (Haven et al., 2020). In exploratory projects like Project 2 and predictive research like Project 3, preregistrations are helpful if the research objective and certain methodological parameters, such as sampling procedure, research design, and available variables for analyses can be specified a priori. For instance, a quantitative marketing scholar working on Project 3 could benefit from a preregistration by ensuring that the large-scale data analysis is planned sufficiently. Researchers can choose a free-format preregistration, creating a custom document by selecting relevant items from Fig. 3 (e.g., research objectives, variables), and expanding on areas like data collection (e.g., for a pre-registered web scraping study).

After data collection and analysis, the researcher creates a document detailing the deviations from the preregistration (Lakens, 2024). There can be good reasons to deviate from preregistration in a way that serves the study's validity such



Notes: The figure illustrates the relative importance of implementing open science practices (planning, PL; documentation, DO; dissemination, DI) in three exemplary marketing research projects. A common practice among all projects is disseminating (DI) the research as a working paper prior to publication and writing practitioner-friendly summaries to enhance the impact of the research.

Fig. 2. Open science building blocks and implementation across three exemplary marketing research projects. Notes: The figure illustrates the relative importance of implementing open science practices (planning, PL; documentation, DO; dissemination, DI) in three exemplary marketing research projects. A common practice among all projects is disseminating (DI) the research as a working paper prior to publication and writing practitioner-friendly summaries to enhance the impact of the research.

as removing non-compliant participants or switching to a more appropriate statistical test. Other differences may include deviations in the final sample sizes, data cleaning decisions, and analysis of additional relationships in the data beyond those originally planned (Banerjee et al., 2020; Claesen et al., 2021; Pham & Oh, 2021).

3.2. Documentation

Enhancing the credibility of marketing research involves documenting research artifacts (i.e., code, data, and other materials) and posting them for public access. The ultimate goal is to provide researchers access to materials adhering to the FAIR principles, which require research artifacts to be findable, accessible, interoperable, and reusable (e.g., Wilkinson et al., 2016). All materials in such directories should fully cover the research project to enable others to comprehend the research workflow and replicate the study. In quantitative research, this may include, for example, lab protocols, questionnaires, data, code, and supplementary analyses. In qualitative research, researchers may document research materials such as interview guidelines, field notes, and transcripts. If not all of the data can be made publicly accessible, researchers must detail how, where, and under what conditions an independent researcher can replicate the steps to access the original data. The information covers any limitations in the data's use and the expected monetary and time costs associated with gaining data access. Scholars and journals can adopt Data Availability Statement templates like those provided by the Social Science Data Editors (2024, https://social-science-data-editors.github.io).

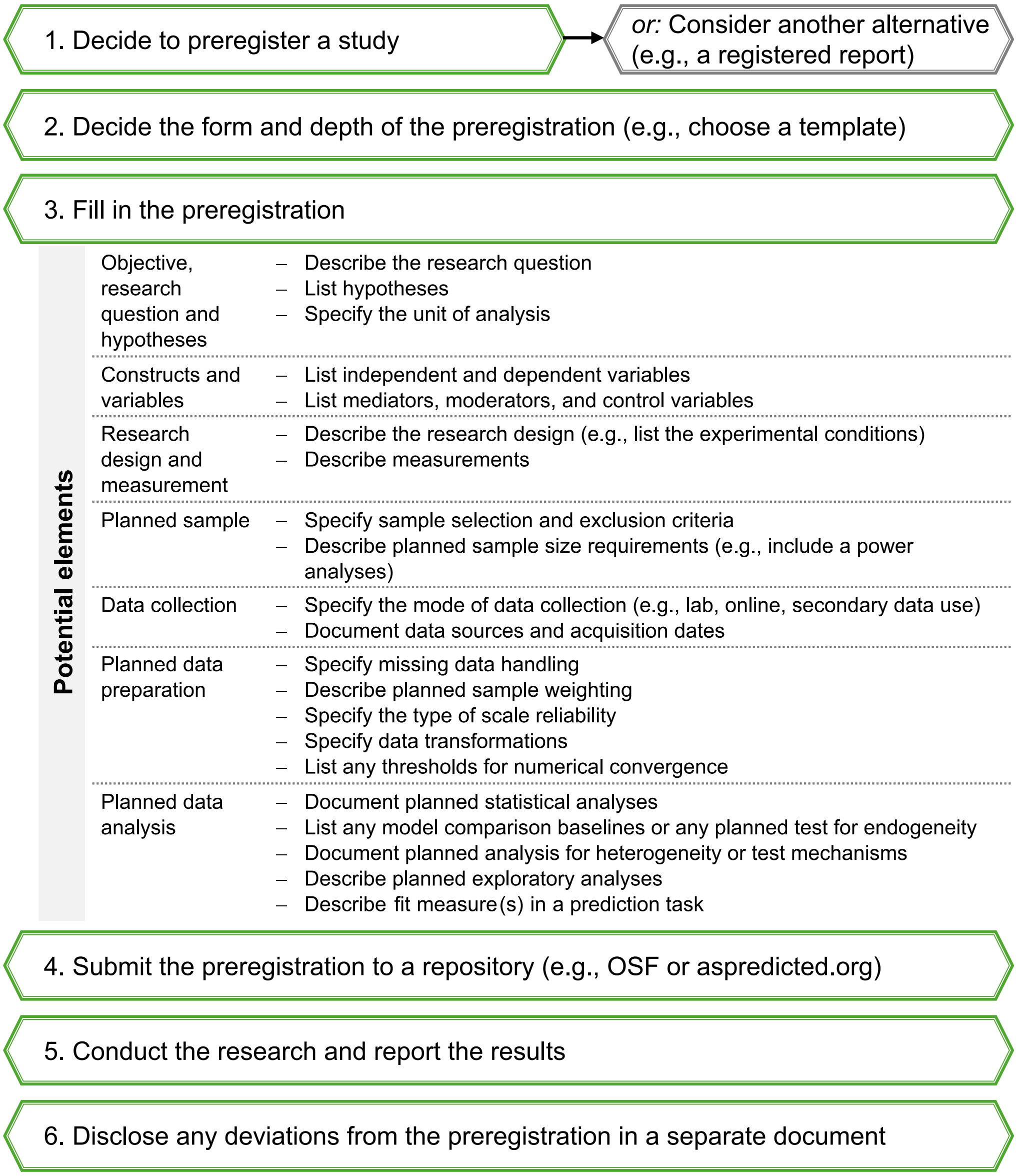


Fig. 3. Exemplary workflow for a preregistration. Notes: A selection of preregistration templates is available in Appendix A2.

In working on a research project, it is helpful to adhere to the principles of file and version management, as summarized in Table 1. Maintaining a clean and organized repository is important, even before posting a replication package. A sound practice is to apply the four-eyes principle: just as papers undergo review by a co-author team before submission, materials, data, and code should be accessible to all members of the team and can be reviewed to ensure they are error-free and comprehensible to others.

Each research project may have different needs concerning its documentation. The researchers involved in the consumer research experiment in Project 1, for example, aim to enable others to replicate their data collection and analysis. They have made all materials, such as questionnaires and stimuli, accessible and provide detailed procedure descriptions (Table 2). Making all materials openly available also includes extracting any information from proprietary software. For example, questionnaire programming software such as Qualtrics allows users to download PDF versions of the questionnaire along with settings and filters. For physical stimuli or hardware such as eye-tracking devices, researchers should ensure that specific models and settings are documented. If data are collected in a lab or in the field, photographs and videos are an easy means to capture the data collection procedures and circumstances. Using a codebook and a README file, researchers can document the variables contained in the dataset and how to run the analysis code.

Table 1
Working principles for a well-maintained project.

1. Computer setup and collaboration
   - Share the full directory with all co-authors (e.g., using Dropbox, Google Drive, or safe file storage provided by the university).
   - Establish shared responsibilities for data and code management (e.g., regular code reviews, trying to run the code written by others)
   - Regularly back up work, ideally with automated, multi-location backups.
   - Use environment variables for passwords and sensitive information; do not include them in any of the source code files.
   - Consider using R Markdown, Quarto, or Jupyter Notebooks to make analyses transparent and easy to follow (e.g., Rule et al., 2019).

2. Data management
   - Do not change any of the raw data files.
   - Deposit the raw files in a secure online repository (e.g., OSF or Zenodo for non-sensitive data; secure alternatives may be available at the university).
   - Make data processing changes in code; document steps if using non-code software (e.g., in a logbook). Never overwrite raw data files.
   - Mark confidential files (e.g., in the filename), ensuring these are not made public accidentally.
   - Use clear, descriptive, and consistent file- and variable names that provide enough context without being ambiguous or overly long. Avoid spaces or special characters.

3. Repository organization
   - Create a README file detailing project structure, file purposes, and reproduction instructions.
   - Maintain a clear directory structure with separate subdirectories (e.g., for data collection, cleaning, and analysis).
   - Keep source code files separate from temporary and final output files to reduce clutter.

4. Maintain your repository
   - Regularly update the README file as the project evolves.
   - Audit code to ensure executability (running code without errors from beginning to end of a script), up-to-date data, proper documentation, and error-free code.
   - Move obsolete files to a "legacy" subfolder or delete them altogether.

5. Check for computational reproducibility
   - Test the workflow to see whether following your own instructions leads to the final results.
   - Test the workflow on different computers and operating systems.
   - Pass it on to a colleague for testing.

6. Advanced applications
   - Automate data processing, analysis, and reporting tasks with code (e.g., R Markdown), reducing the chance of manual errors and ensuring consistency in your workflow.
   - Use version control systems like Git to track changes, revert to previous versions, and collaborate through issues and pull/merge requests. Even basic usage, such as committing changes with clear and meaningful commit messages, can enhance transparency.
   - If possible, use dependency management software (e.g., GNU make or *targets* package in R) to automate your research workflow. For simple projects, use a "starting script" that runs all necessary scripts. If this is not possible, provide specific running instructions.
   - Ensure all paths and filenames used in the source code are *relative*, not absolute paths and filenames (e.g., ../data/dataset1.csv is *relative*, c:\users\me\documents\project\data\dataset1.csv is *absolute*).

Notes: For additional insights on research project and code management, see Gentzkow and Shapiro (2014).

Table 2
Exemplary workflow for documenting study materials that enable others to re-collect and reanalyze data.

1. Provide a detailed step-by-step study procedure for how the data were collected.
2. Provide all materials for data collection in their original form (e.g., stimuli, questionnaires, lab protocols).
   - If applicable, ensure that the materials can be viewed even if specialized software (e.g., Qualtrics) is not available, for example, by providing PDF files of questionnaires and pictures of stimuli.
   - If materials are physical goods or sensory stimuli, describe them as closely as possible. If applicable, provide a recipe or a list of ingredients.
   - If any physical gadget or equipment is in use (e.g., eye trackers or virtual reality glasses), provide information on the exact gadget used and, if available, the product name, producer, and (software) version.
   - For lab or field studies: Provide photographs or videos of the procedure.
3. Provide data and code that allows reproducing the analyses and results.
4. Provide meta-data and a README document that lists all relevant files and describes their contents and purpose.

Table 3
Exemplary workflow for documenting and publishing data.

1. Have a codebook that documents variable names, variable and measurement descriptions (e.g., question wordings), scale and levels (e.g., scale range and anchors), and corresponding summary statistics.
2. Provide at least the raw and processed data sets. If applicable, provide all other relevant data sets (e.g., data sets for specific subgroups). Use easy-to-read file formats (e.g., CSV files), ensuring interoperability.
3. Document all processing steps that happened between the raw and the processed data set (e.g., recordings and variable transformation, data filters). This is best done using code.
4. Provide a README file that clarifies the purpose of each dataset and states the software and version numbers used to create the datasets. If possible, use a README template (e.g., Gebru et al., 2021).
5. Provide meta-data (e.g., data collection date and location).
6. Provide information on the data collection procedure to help others evaluate whether your data fits their research aim.
7. If necessary, anonymize or pseudonymize your data.
8. Add a license for reusing your data, such as the Creative Commons CC-BY-NC for non-commercial reuse.
9. Store all information in an open repository (e.g., OSF, Zenodo), and associate it with a DOI.

Notes: For additional insights, see Goodman et al. (2014).

Researchers in Projects 2 and 3 would specifically focus on documenting their data and analysis workflows. Researchers can start by preparing their data for publication in an accessible and reusable form (Table 3). This process requires describing the sources of each dataset, providing codebooks that detail all variables used in the analysis, and providing all relevant files (e.g., raw and processed data sets) in a commonly used format such as CSV (Vilhuber et al., 2022). Researchers should also document all processing steps necessary to transform raw data into the data used in the final analysis. The data transformation and analysis code should be accompanied by clear documentation, including a file explaining how to execute the code from start to finish, with comments throughout to clarify its functionality and the rationale behind its structure (Martin, 2009; Thomas & Hunt, 2019). To ensure that data and code are findable and citable, researchers may associate a DOI with them and choose a license that enables others to reuse their data with attribution (e.g., Creative Commons, CC-BY-NC, for citable, non-commercial use, while allowing the creation of derivatives such as data sets combining the original data).

3.3. Dissemination

Disseminating research findings includes communicating them within the academic community, as well as to practitioners, policymakers, and the general public (see Table 4 for an overview).

Researchers can actively share preprints on servers such as SSRN, arXiv, or PsyArXiv, thus promoting early visibility and discussion of research findings. Preprints can be updated after the authors have made changes to the manuscript during the revision process or due to community engagement (e.g., discussing articles on social media or on PubPeer; https://pubpeer.com).

Open-access publishing is an important way to make research papers accessible. APCs, however, are often high, and researchers should consider corresponding funding opportunities (e.g., DEAL in Germany). If paying the APCs is not an option, researchers can offer the author version of a manuscript on their personal website. Most publishers specifically allow researchers to share the final author version of a paper and also allow the submission and maintenance of preprints. Moving all supplementary materials to an open repository such as the OSF or Zenodo also helps to ensure public accessibility since authors retain full control of their publication.

To communicate their findings to practitioners, policymakers, and the general public, individual researchers can engage in various methods of science communication. For example, they can write blogs, write for practitioner outlets, or be available for interviews and panel discussions. Many news outlets and academic associations already support science communication and offer platforms and formats that target academic audiences as well as practitioners and the general public. Examples include podcasts such as "Up Next," which features recent papers in the *International Journal of Research in Marketing*, "How I Wrote This" by the American Marketing Association (AMA), as well as "AMS Illuminations" and "AMS Sparks" by the Academy of Marketing Science (AMS). Distributing marketing knowledge to the public also includes making educational resources or recorded short lectures and tutorials openly available. With these materials, researchers can reach audiences beyond their institution and inspire students from other fields to engage with marketing research.

4. Advanced applications and emerging open science practices

4.1. Alternatives to preregistration and registered reports

Preregistrations are well-suited for confirmatory hypothetico-deductive research in which data and result structures can easily be anticipated. Exploratory research and predictive modeling, however, often require a more flexible approach to data collection and analysis. Preregistration can help to commit to a specific research objective and carve out a methodological structure before data collection. Identifying and validating more flexible but still rigorous alternatives to preregistration is thus an active area of investigation that offers the potential to contribute toward mitigating researcher biases and controlling researchers' degrees of freedom.

Several approaches have been recommended for improving the transparency of data analysis. For example, establishing *Standard Operating Procedures* to guide analytic decisions—such as considering the use of clustered standard errors or deciding between one- versus two-tailed significance tests—promote transparency and credibility (Lin and Green, 2016). In a *Split Sample Approach*, researchers partition the data into an exploratory sample for unconstrained analysis and a holdout sample where analysis is conducted to confirm hypothesized relationships or predictions (Anderson and Magruder, 2017; Fafchamps and Labonne 2017). If a validation sample is externally deposited before a study begins, it could give further credibility to the study. *Blind Analysis* involves hiding some aspects of the data—such as whether respondents belong to the treatment group or the control group—to prevent investigator biases in their analysis (Dutilh et al., 2021; Klein & Roodman, 2005).

As an alternative to registered reports tied to a specific journal, researchers can also opt for a "Peer Community In" (PCI) registered report (rr.peercommunityin.org), which is journal-independent. Manuscripts that receive an in-principle acceptance via this process include a publication recommendation that authors can use to select a journal for publishing their final paper without any further peer review (PCI-friendly journals such as *Advances in Methods and Practices in Psychological Science*) or journals that invite promising manuscripts for publication (PCI-interested journals such as *Nature Human Behaviour*).

Table 4
Exemplary actions to disseminate research findings in the academic community, to practitioners, policymakers, and the general public.

To academic audiences	To practitioners, policymakers, and the general public
Interact with working papers and preprints - Share preprints, working papers, slide decks, and posters through platforms like arXiv, PsyArXiv, OSF Preprints, ResearchGate, SSRN, or conference repositories. - Subscribe to updates from preprint servers. - Cite preprints in your own work. - Provide feedback on preprints.Publish open access - Share the author's version of published manuscripts online. - Use open access funding.	Engage in science communication - Write for non-academic audiences (e.g., write articles in practitioner magazines). - Serve as an expert in news and media outlets or podcasts. - Actively send practice-oriented one-pagers on your research papers to news outlets.Take part in or organize events - Take part in or organize workshops or events with marketing academics and practitioners. - Take part in practitioner conferences or symposia and serve as a speaker.
Applicable for academic audiences as well as practitioners, policymakers, and the general public	
Build a social media presence - Use social media (e.g., LinkedIn, X) to share research findings and engage within and beyond the academic community. - Visualize your research in short videos, infographics, or comics of your findings.Share educational resources - Create and maintain a research blog or website to disseminate findings and educational materials. - Develop webinars and online courses to share knowledge with broader audiences.	

Adopting registered reports in marketing research on a grander scale requires coordinated efforts from multiple parties—including journals. Researchers can also contribute to this development by organizing special issues that offer registered reports within a thematic area. These efforts may prove especially beneficial in fields where concerns have been raised about publication biases (e.g., nudging; Maier et al., 2022) or in areas characterized by distinct research clusters with differing perspectives on the same phenomenon (e.g., context effects; Evangelidis et al., 2024). In the future, marketing researchers can adapt the registered report format to suit their research traditions. For instance, using registered reports for predictive purposes can separate planned methodology from data analysis. For exploratory research, early methodological exchanges with reviewers can help identify alternative models or data sources.

4.2. Computational reproducibility, secondary outputs, and data management

In addition to sharing data and code, researchers can complement their work with reproducible research workflows compatible across various operating systems and software versions. Documenting a computationally reproducible research workflow starts with adopting version control (e.g., Git), writing code with standardized and clear writing styles passing so-called "unit tests" that verify the accuracy of the code's output, using dependency management software (e.g., make, targets), and archiving the required data or materials for future access (Hunter-Zinck, et al., 2021; Taschuk & Wilson, 2017). Ideally, researchers share their code as a research pipeline in which the paper's final set of tables and figures and any related "by-product" (e.g., cleaned data sets) can be automatically obtained by executing code on the project's raw data (Gentzkow & Shapiro, 2014). In constructing their code, researchers can use open-source software when possible, enabling a larger pool of researchers to access and use their work (see also Barker et al., 2022). In Table A3 in the Appendix, we have compiled a range of tools and packages that can enhance research reproducibility at various stages of project development. Institutions can also support researchers in adhering to these practices (Baker et al., 2023; Digital Science, 2023).

Moving beyond the computational reproducibility of a project, which enhances the transparency and credibility of empirical results, marketers can make the data and code an integral element of their research output to enrich the original article. This practice is already common for articles introducing new methods. For example, Lu et al. (2023) propose a new approach to retail price decomposition, which they make publicly available via an R package on GitHub. Adler and Sarstedt (2021) supplement their article with an interactive web app using Shiny (https://shiny.posit.co/), which facilitates building interactive web apps straight from R and Python. While few marketers release software packages, partly due to the lack of recognition, journals like *SoftwareX* and the *Journal of Statistical Software* provide platforms for such contributions. Marketing journals could also adopt sections dedicated to software publication, as *Computational Economics* does, or publish database submissions as is the current practice at *Marketing Science* (e.g., Bradlow, 2008; Lovett et al., 2014). Outside marketing, other fields have established separate data-focused journals. For example, the Elsevier journal *Data in Brief* publishes short data articles that describe and provide access to research data from various fields of science, including agriculture, engineering, and materials science.

Another promising way to allow other researchers to build upon research in cases where data is not sharable is to provide anonymized or synthetic data, both of which aim to preserve privacy while making the data usable for analysis.[3] Data

[3] Data anonymization is the process of protecting private or sensitive information by erasing or encrypting identifiers that connect an individual to stored data. Common techniques include generalization (reducing data precision), suppression (removing certain fields), pseudonymization (replacing identifiers with pseudonyms), data masking (hiding parts of the data), and perturbation (adding noise to numerical data).

anonymization has been used in healthcare, finance, and social sciences research, as well as in marketing research. For example, the NielsenIQ data provided by the Kilts Center at the Booth School of Business through commercial subscriptions uses data anonymization to mask retail store identification in the Retail Scanner Data. An important challenge with data anonymization is the risk of re-identification, especially in large or complex datasets. Additionally, legal considerations may limit the utility of anonymized data for reproducing research findings or for new analyses.

In contrast, synthetic data involves the creation of artificial datasets that mimic the statistical properties and patterns of real data without containing actual identifiable information. This approach generates new data points using machine learning algorithms such as Generative Adversarial Networks or Variational Autoencoders, statistical and econometric models, or stochastic differential equations.[4] Synthetic data can replicate complex structures and relationships found in original datasets and can generate rare scenarios or edge cases present in real-world data. While synthetic data can provide strong privacy protections by eliminating identifiable information, challenges include ensuring the synthetic data accurately represents the original data's characteristics and maintaining its utility for intended applications (Lucini, 2021; Schneider et al., 2018). At the same time, synthetic data may not protect a company's sensitive information, as important summary statistics and correlations are preserved in such data.

4.3. Big-team science

A goal of open science is to help researchers accumulate knowledge through improved collaboration between researchers through sharing materials, data, code, and knowledge. These efforts may extend to broader collaborations between research groups through big-team science projects. Big-team science combines the knowledge and resources of multiple research groups, which promises an accurate and transparent picture of an effect's size and variability, mitigating publication bias and selective reporting (Kvarven et al., 2020).

In big-team science projects, a large number of researchers from multiple research groups or labs collaborate to address a single research objective of broader interest (Duckworth & Milkman, 2022; Forscher et al., 2022)—see Table 5 for an overview of different project types. Such projects may involve multiple labs that collect data from different sources to replicate a specific effect (e.g., Klein et al., 2014; Verschuere et al., 2018), investigate sources of heterogeneity between samples (e.g., Klein et al., 2018), or compare effects from multiple interventions on a predefined target outcome (megastudies; e.g., Milkman et al., 2021). Milkman et al. (2022), for example, involved multiple research groups that designed 41 interventions in two megastudy field experiments that examined the effectiveness of text message-based nudges on vaccination uptake on more than 700,000 patients. Big-team science projects may also come in the form of many-analysts studies in which multiple researchers test the same model using the same data but different methods (e.g., Huntington-Klein et al., 2021; Menkveld et al., 2024; Sarstedt et al., 2024; Silberzahn et al., 2018). For example, the *International Journal of Research in Marketing*, in collaboration with AiMark, provides a common data set and invites research teams to estimate the price elasticity of meat substitutes while clearly documenting their analytical choices (elasticity-open-science.com). This initiative aims to produce answers to the substantive question and an analysis of how analysts' choices influence these answers (Pauwels et al., 2024). In Table A4 in the Appendix, we provide a set of steps to put such big-team science projects into practice.

Successful projects often involve contributions from multiple research fields and can leave a lasting impact on a discipline. A prominent example is the Reproducibility Project Psychology (Open Science Collaboration, 2015), which tested the replicability of 100 psychological studies and found that only 39 % of the replications were successful. However, a re-analysis of the data by Gilbert et al. (2016) suggested that, given the study's methodology, the evidence actually indicated high reproducibility rates. In response, Anderson et al. (2016), while critiquing certain aspects of Gilbert et al.'s (2016) statistical approach, acknowledged that both optimistic and pessimistic conclusions about reproducibility were possible, and neither was yet warranted. Despite differing interpretations, the project played a pivotal role in psychology's shift toward open science.

5. Toward an open science culture in marketing research

Implementing open science and changing research practices is a massive undertaking. It took researchers in psychology over a decade to create awareness for and initiate a shift toward open science. Psychology has adopted preregistration, data sharing, and preprint servers such as PsyArXiv. Many psychology journals (e.g., *Psychological Science*) have implemented open science practices to increase accountability and transparency (e.g., Hardwicke & Vazire, 2024). Economics has seen the *American Economic Association* establish a registry for randomized controlled trials (https://www.aeaweb.org/journals/policies/rct-registry), leading economic journals have adopted a common code and data availability standard (https://datacodestandard.org/), and there is a strong working paper culture. Such a transition requires a deliberate effort from the authors and support from academic associations, institutions, and journals.

[4] Example packages to generate synthetic data include synthpop (Nowok et al., 2016) and Synthetic Data Vault (Patki et al., 2016)—see Grund et al. (2024) for a discussion and example use case for synthetic data generation in psychological research.

Table 5
Types of big-team science projects.

Project type	Description	Example projects
Many-labs project	Multiple researchers follow the same data collection procedure. – Coordinating researchers typically provide the materials (translations or lab-specific instruction might be outsourced to participating researchers), merge the collected data, and analyze the data. – Participating researchers typically provide data collection resources (e.g., supply a specific number of respondents) and, if applicable, adapt lab-specific instructions.	Klein et al. (2014); Verschuere et al. (2018)
Many-analyst project	Multiple researchers receive a predefined data set to analyze a research question in any manner that they see fit. – Coordinating researchers provide all necessary data and materials as well as merge the results from all analyses. – Participating researchers analyze the data and provide a reproducible analysis workflow.	Huntington-Klein et al. (2021); Sarstedt et al. (2024); Silberzahn et al. (2018)
Megastudy	Multiple researchers test interventions for a real-world problem. – Coordinating researchers provide the research objective and overarching coordination. – Participating researchers suggest interventions. Data collection can be outsourced to other participating researchers.	Milkman et al. (2021)

Notes: For more information on big team science projects, see Forscher et al. (2022).

To foster a robust open science culture in marketing research, the field needs to overcome a range of potential impediments. One factor impeding the cultural change in marketing is the incentive misalignment evident in individual outputs and across the entire spectrum of research activity (Shaw & Nave, 2023). One potential solution is to redefine research output to include not only the published manuscript, but also all related research tools, materials, data, and code. Further, marketing researchers' internal institutional incentives are closely tied to the number rather than the quality of their publications (Stremersch et al., 2021), encouraging in-house data retention to maximize the potential for multiple publications from one dataset. For researchers working with proprietary data, this practice is often necessitated by non-disclosure agreements (NDAs) or data privacy concerns that preclude data sharing. Researchers may also fear that replication failures or exposure of coding errors may damage their reputations and careers. This issue creates a tension between an individual's interest in being perceived as a competent researcher and the error-corrective nature of science.

While open science practices promise important benefits, an overly strict interpretation of these principles may hinder scientific advancement in subdisciplines that engage in practice-oriented and non-deductive research (Golder et al., 2023). Researchers may feel discouraged from pursuing nonconforming studies, which could stifle the creativity and opportunistic thinking that often drives applied research (Guzzo et al., 2022). Marketing research has a longstanding tradition of delivering valuable insights and contributions to business practice through identification of empirical generalizations (Hanssens, 2018; Bass and Wind, 1995). Striking a balance between embracing open science principles and preserving the flexibility required for applied research is essential to fostering continued innovation and progress while also increasing transparency.

Recent developments in marketing highlight additional ways in which a more open culture can be fostered. First and foremost, journals and academic associations serve as catalysts for change since they can enforce and enable open science practices. Besides establishing new publication formats (e.g., datasets, registered reports, software packages), journals may appoint dedicated data and code editors, as seen in the *American Economic Review, Management Science,* and other journals, to ensure reproducibility and accessibility. Academic societies such as the AMA, AMS, and the European Marketing Academy (EMAC) could create large, centralized repositories for code and data in a similar way as the repository the Inter-university Consortium for Political and Social Research (ICPSR, see openicpsr.org) operates for articles published in the American Economic Association journals. Furthermore, the Marketing Science Institute (MSI) and other marketing scholarship institutions could promote openness by encouraging authors to share their data alongside working papers. Organizations that license data for academic research (e.g., AiMark, Kilts Center) could establish secure environments for archiving replication files, ensuring that the exact (NDA-protected) data and code are preserved. NDAs could then be negotiated between these organizations and external replicators, allowing for controlled access to the data for independent verification.

Journals and associations can further facilitate developing and coordinating big-team science infrastructures. To date, big-team science projects are typically independently organized by a team of authors and submitted to a journal as a finished paper or in a registered report format. These projects are organized in a decentralized manner so that a specific project can dissolve afterward, which makes organizing the collaboration resource-intensive. Journals and academic societies can consider building a standing panel of researchers who would be willing to contribute to big-team efforts. With a journal's commitment to publish a big-team science manuscript independently of its results, involvement in the project could be attractive to authors. Such a publication may contribute to the journal's reputation by generating follow-up discussions or commentaries. Collaborations could range from data collection and analysis, which has been the norm, to theory development and discussion, by allowing many authors to comment on an emerging framework or theoretical advancement in a structured form.

Journals can also contribute to early dissemination by engaging with open peer review (Ross-Hellauer & Görögh, 2019). The journal *Meta-Psychology*, for example, has a publication and review tracker for all submissions to the journal. *Meta-Psychology* is independent of major publishers, fully relies on the engagement of the psychological community, and provides open-access publishing without article processing fees.

Research institutions could foster an open research culture by establishing robust research support structures and funding to support the transition to open science, including specialized positions dedicated to tasks such as efficient cataloging and data sharing. Hosting research workshops and replication labs that bring together researchers from marketing and other fields can also help establish a more open culture and support the dissemination of research techniques and practices across disciplines. For example, the *Framework for Open and Reproducible Research Training* (FORRT; https://forrt.org/) offers a variety of multi-disciplinary open science training and educational materials. Consortiums such as the *UK Reproducibility Network*, projects such as *The Turing Way*, and university initiatives such as the *LMU Munich Open Science Center* or *Tilburg Science Hub* are also the environments that support cultural change across disciplines. PhD seminars can serve as forums for embedding open science principles into the core academic discourse. Actively engaging in broader open science initiatives can extend the impact of these efforts. For instance, projects such as the Reproducibility Project: Psychology (Open Science Collaboration, 2015) or the Institute for Replication (https://i4replication.org/) validate findings across disciplines and contribute to the field's collective advancement.[5]

Research faculty play a key role in transforming our academic system. Teaching materials that lower the costs of adopting open science (e.g., syllabi, course materials, assignments) can also be made publicly available, leading to a more equitable learning environment. For example, engaging students in replication projects or asking them to release self-collected data to the public teaches lessons on the importance of reproducibility and sharing. PhD students further form their first impression of marketing research from contact with their advisors and learn how to navigate research and the academic publication system from recurring interactions with senior academics. For example, encouraging participation in replication games, by research faculty, researchers, and graduate students, has been shown to help document meta-scientific evidence on the transparency and reproducibility of published marketing research (Brodeur et al. 2024b). Not practicing open science can also lead to the perpetuation of discouraging myths about the narrow applicability, infeasibility, or needlessness of open science that reportedly prevails in editorial boards (for an overview see Hüffmeier & Mertes, 2023; Torka et al., 2023). Scholars should address these concerns and help others navigate the evolving publication landscape that professes general support for open science and its often-hesitant application. Teaching a responsible and transparent way of doing research is vital to ensure the longevity and relevance of academic marketing research.

6. Conclusion

In this paper, we offer practical recommendations on adapting and adopting open science practices in marketing research to improve collaboration and dissemination of knowledge, and address the increasing complexity of data and research technologies. Our focus is to provide an overview of open science practices, emphasizing planning, transparent documentation of code, data, materials, and the open dissemination of research findings and materials. We describe specific actions that individual authors can take toward integrating open science in their research.

We recognize that while open science practices promise benefits, researchers may face different costs in implementing them (e.g., documenting complex research workflows vs. simple analysis) and may also weigh costs and benefits differently. In fact, the authors of this paper are not in agreement on which open science practices can or should be adopted and implemented by the marketing field.

One point of view suggests that the value of reproducibility and transparency in scientific research cannot be overstated (Miguel et al., 2014; Munafò et al., 2017; Wagenmakers et al., 2021). Enhancing transparency through open science practices can restore trust in the scientific system and address the credibility debate head-on (Pennington, 2023; Vazire, 2018). Transparency also requires disclosing nonsignificant results or model estimations that do not meet recommended levels of fit. While such results do not prove the absence of an effect, they reduce uncertainty in follow-up studies of the same phenomenon (Sarstedt et al., 2024). The absence of evidence for questionable research practices in certain subfields should not be interpreted as proof that such practices do not occur. Across each research project, researchers make hundreds of conscious or unconscious decisions at each step of the scientific process, all of which could lead to different results (Gelman & Loken, 2014; Schweinsberg et al., 2021). Making researchers' workflows transparent is fundamental for understanding the boundary conditions of observed effects and assessing their generalizability and replicability (Wagenmakers et al., 2021). The necessity of replicable effects is undisputed in the life sciences (Ioannidis, 2018), and similar standards should apply to marketing research.

The second point of view advocates caution, noting that the costs of implementing some open science practices can be high and these practices should be adapted to the needs of specific research projects. While open science practices aim to enhance research integrity and generate more credible results, evidence is needed on the causal effects of open science

[5] The Replication Games format approaches this ideal by organizing a series of one-day events that follow a test-fast, fail-fast principle (Brodeur et al., 2023). The associated Institute for Replication (https://i4replication.org/) provides an infrastructure for bringing together collaborators which makes it easy to participate in such a big-team projects that yield meta-papers summarizing results, see Brodeur et al (2024b).

(Suls et al., 2022). Current concerns include the high costs, low effectiveness, and a general lack of reliable evidence supporting the benefits of some open science practices, urging more research before mandating widespread adoption (Brodeur et al., 2024a; Kahneman, 2014; Suls et al., 2022). Additionally, there is growing recognition of the structural inequities in open science, as not all practices are equally accessible, and transitioning to open science may require resources some researchers and institutions simply do not have (Bahlai et al., 2019). For instance, some researchers conduct multiple preliminary studies before pre-registration, increasing costs and making these practices less feasible for those with limited resources. Some open science practices may also discourage certain research domains and approaches and stifle researchers' creativity and learning from data to improve methods and models (Gelman & Loken, 2014; Golder et al., 2023; Guzzo et al., 2022; Hanssens, 2018).

In conclusion, changes are coming to how marketing research is conducted and reported. Funding agencies and the public are demanding more accountability and greater openness, and the open science paradigm may offer a potential answer to their demands. We hope our paper will motivate academic discussions about the adoption of open science in marketing, including the development of marketing-specific solutions that preserve and improve not only the reliability and reproducibility of marketing research but also its relevance, creativity, and, ultimately, its impact on business practice.

Disclosures

While preparing this work, the authors used ChatGPT for initial copy-editing and drafting tables based on their own ideas. After using this tool/service, the author reviewed and edited the content as needed and take full responsibility for the content of the publication.

CRediT authorship contribution statement

Lachlan Deer: Writing – review & editing, Writing – original draft, Visualization, Validation, Investigation, Data curation, Conceptualization. **Susanne Adler:** Writing – review & editing, Writing – original draft, Validation, Investigation, Data curation, Conceptualization. **Hannes Datta:** Writing – review & editing, Writing – original draft, Validation, Supervision, Resources, Project administration, Investigation, Funding acquisition, Conceptualization. **Natalie Mizik:** Writing – review & editing, Writing – original draft, Validation, Project administration, Investigation, Conceptualization. **Marko Sarstedt:** Writing – review & editing, Writing – original draft, Validation, Supervision, Resources, Investigation, Funding acquisition, Conceptualization.

Data availability

No data was used for the research described in the article.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

Table A1
Open Science Policies in Major Marketing Journals.

Journal	Planning (preregistration)[1]		Documentation (code, data, materials)			Dissemination (open access)
	Required	Default Publicly Available	Required	Access During Review	Default Publicly Available	Open access available
Journal of Consumer Research	Encouraged	No	After revise and resubmit	Editor	No	Yes
Journal of Marketing Research	No	No	After cond. accept	Coeditor & review team	No	Yes
Journal of Marketing	No	No	After revise and resubmit	Editor and Associate Editor	No	Yes
Marketing Science	No	Yes	After acceptance	No	Yes	Yes
Journal of Consumer Psychology	Encouraged	No	After revise and resubmit	Editor & review team	No	Yes
International Journal of Research in Marketing	Encouraged	No	No	No	No	Yes
Management Science	No	Yes	After acceptance	No	No	Yes
Journal of the Academy of Marketing Science	No	No	No	No	No	Yes
Marketing Letters	Encouraged/ Yes[2]	Yes	First Submission	Review Team	No	Yes
Journal of Retailing	No	No	No	No	No	Yes

Notes: The table summarizes the open science policies of the *International Journal of Research in Marketing and* all marketing journals listed in the FT50 (January 2024). Policies indicated are in effect as of September 2024.
[1] The *International Journal of Research in Marketing* and the *Journal of Consumer Research* also offer registered reports (Pauwels et al., 2024).
[2] Encouraged for the first submission, required on re-submission.

Table A2
Preregistration templates.

Name (and reference)	Description
Generic templates	
AsPredicted preregistration (https://aspredicted.org)	Easy-to-implement template of eight questions.
OSF preregistration template (Bowman et al., 2020)	A more extensive template with a focus on methodology and data analysis.
Preregistration in social psychology (van't Veer & Giner-Sorolla, 2016)	A template with a focus on methodology and data analysis.Includes dedicated sections to describe data analysis plans for multiple hypotheses.
OSF free format preregistration (https://osf.io/zab38/wiki/home/)	Provides minimal guidance and is useful for very specific, individualized preregistration plans.
Research-design specific templates	
Qualitative research preregistration (Haven et al., 2020)	Template for qualitative research detailing, for example, the data collection, analytical process, and credibility strategies.
Replication recipe (Brandt et al., 2014)	Template with two parts (pre-completion and post-completion) for replication studies.
Secondary data preregistration (van den Akker et al., 2021)	Template focusing on the dataset description and plans for secondary analyses.
Generalized systematic review registration form (van den Akker et al., 2023)	Extensive template concerning all stages of a systematic literature review or meta-analysis.

Notes: Templates can, for example, be submitted at https://osf.io/registries via a predefined form directly available from the OSF or by submitting any file format under an OSF free format preregistration.

Table A3
Selected components and tools for reproducible research workflows.

	Description	How to get started
Version control	A system that records changes to files over time, allowing retrieval of specific versions later.	Begin by using Git, a widely used version control system. Install Git and create a repository for your project on GitHub. You can also use Git from the RStudio IDE.
Dependency Management and Automation	Manages library and package versions required by the project to ensure consistency across environments. Additionally, it specifies how to run the source code files and in which order.	For dependencies, Python users can use pip or Conda with a requirements.txt or environment.yml. R users should consider renv for dependency management. Automate workflows using Make or Snakemake, and for R, use drake or targets to automate data analysis and report generation.
Containerization	Packages code, dependencies, and system libraries into a container for consistency across environments.	Start with Docker. Install Docker, then create a dockerfile to specify an environment that includes R and/or Python packages to be run in a container.
Documentation	Provides detailed information about the project to ensure understanding and replicability.	Write a comprehensive README file for the project that includes an introduction, setup instructions, usage, and contribution guidelines. Use Markdown for formatting, which is supported by both GitHub and RStudio. Start with templates (e.g., Gebru et al., 2021).

Tabble A3 (*continued*)

	Description	How to get started
Automated Testing	Writing tests to ensure the code functions as expected.	For Python, begin with a testing framework like pytest. For R, use the testthat package to write tests for your R functions. Integrate these tests into your development process.
Continuous Integration (CI)	Automates the integration of code changes from multiple contributors by running tests automatically.	Start by using a service like GitHub Actions. Set up a CI pipeline that runs automated tests every time code is pushed to your repository.

Notes: The components of a reproducible research workflow are flexible and can be exchanged by different tools. They can be adopted gradually. Rather than immediately starting with version control and dependency management, researchers can use a transparent directory structure or use dynamic documents such as Markdown or Quarto that explicate code and results as first steps. For a selection of documented reproducible research workflows, we refer to Van Lissa et al. (2021) who introduce a template and R package. In addition, Peikert and Brandmaier (2021) offer a template for reproducible research combining Python and R, including dependency management (with make), version control (via GitHub), code execution in multiple statistical packages, and containerization (with Docker) for consistent software environments. For other best practices, see Sandve et al. (2013), Schwab et al. (2022), Wilson et al. (2014), and Wilson et al. (2017).

Table A4
Exemplary workflow for a big-team science project.

Being a coordinator	Being a participating researcher
1. Identify a research objective and an appropriate type of Team Science project. 2. Outline the exact research procedure and identify which roles and tasks individual researchers can take: – Tasks that should remain with the coordinators include, for example, overall communication, project and time management, supervision, preparing and checking materials, data merging, and writing the first manuscript draft. – Tasks that could be outsourced to participating researchers include, for example, preparing specific materials such as translations, data collection, or specific analyses. 3. If applicable, prepare a registered report. 4. Set up an infrastructure for communication and sharing files among all researchers who are involved in the project. 5. Gather collaborators as participating researchers. 6. Prepare all necessary files (e.g., instructions, materials, data) for data collection and share those with the participating researchers. 7. Merge the data from all participating researchers. 8. Compile the overall report and allow the participating researchers to provide feedback.	1. Learn about ongoing or upcoming projects and reach out to coordinators or sign-up for the project. 2. Sign up for a role that you can take as a participating researcher (e.g., aid in the preparation of materials including translations, support data collection, providing an analysis). 3. Secure the appropriate resources (e.g., funding for data collection) 4. Conduct the data collection, analysis, etc. 5. Provide all relevant data to the coordinators. 6. Provide feedback on the final report.

Notes: Non-exhaustive tips for planning and conducting a big-team project. For more information, see Forscher et al. (2022).

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