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ARIADNE: A Scientific Navigator to Find Your Way Through the Resource Labyrinth of Psychological Sciences

Helena Hartmann[1], Çağatay Gürsoy[2,3,4,5], Alexander Lischke[6,7], Marie Mueckstein[8,9], Matthias F. J. Sperl[10,11,12], Susanne Vogel[7,13], Yu-Fang Yang[14], Gordon B. Feld[2,3,4,5], Alexandros Kastrinogiannis[15,16], and Alina Koppold[15]

[1]Clinical Neurosciences, Department for Neurology and Center for Translational and Behavioral Neuroscience, University Hospital Essen, Essen, Germany; [2]Department of Clinical Psychology, Central Institute of Mental Health, Medical Faculty Mannheim, Ruprecht Karl University of Heidelberg, Mannheim, Germany; [3]Department of Psychiatry and Psychotherapy, Central Institute of Mental Health, Medical Faculty Mannheim, Ruprecht Karl University of Heidelberg, Mannheim, Germany; [4]Department of Addiction Behavior and Addiction Medicine, Central Institute of Mental Health, Medical Faculty Mannheim, Ruprecht Karl University of Heidelberg, Mannheim, Germany; [5]Department of Psychology, Ruprecht Karl University of Heidelberg, Heidelberg, Germany; [6]Institute of Clinical Psychology and Psychotherapy, Medical School Hamburg, Hamburg, Germany; [7]Department of Psychology, Medical School Hamburg, Hamburg, Germany; [8]Department of General and Neurocognitive Psychology, International Psychoanalytic University Berlin, Berlin, Germany; [9]Department of Psychology, University of Potsdam, Potsdam, Germany; [10]Department of Clinical Psychology and Psychotherapy, University of Giessen, Giessen, Germany; [11]Center for Mind, Brain and Behavior, Universities of Marburg and Giessen (Research Campus Central Hessen), Marburg, Germany; [12]Department of Clinical Psychology and Psychotherapy, University of Siegen, Siegen, Germany; [13]ICAN Institute for Cognitive and Affective Neuroscience, Medical School Hamburg, Hamburg, Germany; [14]Division of Experimental Psychology and Neuropsychology, Department of Education and Psychology, Freie Universität Berlin, Berlin, Germany; [15]Institute for Systems Neuroscience, University Medical Center Hamburg-Eppendorf, Hamburg, Germany; and [16]Department of Neurology, Max Planck Institute for Human Cognitive and Brain Sciences, Leipzig, Germany

Abstract

Performing high-quality research is a challenging endeavor, especially for early career researchers, in many fields of psychological science. Most research is characterized by experiential learning, which can be time-consuming, error-prone, and frustrating. Although most institutions provide selected resources to help researchers with their projects, these resources are often expensive, spread out, hard to find, and difficult to compare with one another in terms of reliability, validity, usability, and practicability. A comprehensive overview of resources that are useful for researchers in psychological science is missing. To address this issue, we created ARIADNE: a living and interactive resource navigator that helps to use and search a dynamically updated database of resources (https://igor-biodgps.github.io/ARIADNE). In this tutorial, we aim to guide researchers through a standard research project using ARIADNE along the way. The open-access database covers a growing list of resources useful for each step of a research project, from the planning and designing of a study, over the collection and analysis of the data, to the writing and disseminating of the findings. We provide (a) a step-by-step guide on how to perform a research project (in the fields of biological psychology and neuroscience as a case example but with broad application to neighboring fields) and (b) an overview of resources that are useful at different project steps. By explicitly highlighting open-access and open-source resources,

Corresponding Author:
Helena Hartmann, Clinical Neurosciences, Department for Neurology and Center for Translational and Behavioral Neuroscience, University Hospital Essen, Essen, Germany
Email: helena.hartmann@uk-essen.de

we level the playing field for researchers from underprivileged countries or institutions, thereby facilitating open, fair, and reproducible research in the psychological sciences.

Keywords
brain, early career researcher, education, learning, neuropsychology, neuroscience, research cycle, research process, resource, tool, open materials

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A comparison between research projects conducted 2 decades ago and those of today reveals a marked increase in the demands placed on *early career researchers* (ECRs; Weissgerber, 2021). This can be attributed, in part, to factors such as the need for larger sample sizes (Fan et al., 2014; Marx, 2013; Zook et al., 2017), the incorporation of novel methods such as preregistration or dissemination (Ross-Hellauer et al., 2020; Tripathy et al., 2017), and the growing use of advanced computational and statistical techniques (e.g., machine learning; Bolt et al., 2021; Bzdok & Yeo, 2017) and cutting-edge technologies, such as virtual reality (Matthews, 2018). All of these factors contribute to an increased time commitment required to successfully undertake such research endeavors (Powell, 2016). Accordingly, the motivation and eagerness many ECRs feel during their first years is more and more often accompanied by feelings of being overwhelmed (Kismihók et al., 2022; Levecque et al., 2017) because many project choices have to be made and a variety of skills need to be learned quickly that determine the long-term success of one's first research project.

At this stage, however, most ECRs lack the necessary expertise and experience to make such important decisions. Moreover, learning the "language of science" can be difficult (Parsons et al., 2022; see also Table 1). In addition, institutions and supervisors often provide researchers with a relatively fixed array of conventionally used resources, such as subscription-based or in-house software. These tools are often expensive and/or bound to the institution itself (i.e., may become unavailable when the researcher changes institutions). These limitations in resources might not only impede but also prevent good scientific practice. Although many *open-access* tools have been proposed to facilitate project work, these resources are often spread out and hard to compare with each other in terms of reliability, validity, usability, and practicality (but see a collection of open-science-related resources from the Framework for Open and Reproducible Research Training spanning multiple fields). Taken together, dealing with these difficulties may be time-consuming and create a (potentially error-prone) resource labyrinth, further exacerbating the uncertainty of how and with which tools high-quality science can be conducted.

The Resource

ARIADNE

Therefore, a comprehensive overview of curated resources is warranted. ARIADNE is a living (e.g., continuously updated with new contributions from the research community) resource navigator that helps to search a dynamically updated database of resources (see also Fig. 1 and exemplary resources marked with "➜" in the subsequent text). We named our tool "ARIADNE" because we aim to help researchers navigate the "labyrinth" of research tools and resources, much like the mythological Ariadne helped Theseus navigate the labyrinth (e.g., Rose et al., 2015). Our tool is available as a dynamic interface for easier use and searchability, was developed by researchers in the fields of biological psychology and neuroscience, and has wider applications to all fields of psychological science. The open-access database covers a constantly growing list of resources that are useful for each step of a research project, from the planning and designing of the study, over the collection and analysis of the data, to the writing and disseminating of the findings. We include a broad range of tools but put a specific emphasis on open and reproducible science practices because these practices have become more and more valued and even mandatory in many fields of psychological science (Kent et al., 2022).

Technical specifications

Detailed usage instructions and the corresponding source code are freely available online (https://github.com/IGOR-bioDGPs/ARIADNE). The tool is divided into two sections: a web-hosted Jupyter Book detailing the 10 steps of a research project shown in blue on the left side of Figure 1 and in Table 2 and a Cytoscape network showcasing the steps dynamically and interactively. We

Table 1. Mini Glossary of Science-Related Terminology, Sorted Alphabetically

Term	Definition	References
Article/author processing charges (APCs)	A fee charged to authors by a publisher in exchange for publishing and hosting an open access article.	Parsons et al. (2022)
Big team science	A method that engages a considerable number of contributors, who may be situated in diverse research environments, including laboratories, academic institutions, and academic disciplines, and representing a range of cultural and geographical backgrounds.	Forscher et al. (2023)
Corresponding author	The corresponding author is typically the researcher who takes primary responsibility for communication regarding the manuscript, during both prepublication and postpublication phases. This usually includes communication with the publisher and the readers and handling requests for data sharing. Note that different journals may have different requirements for corresponding authors.	Pain (2021)
Cover letter	A letter to the editor of a scientific journal that is submitted together with a manuscript that outlines the importance of the study and summarizes key findings and contributions to the field. Some journals explicitly require such a letter, and others actively discourage it.	Palminteri (2023)
CRediT statement	A taxonomy of 14 roles that can be assumed when being part of a research project. The statement can be included at the end of a manuscript to transparently report which author assumed which roles.	Brand et al. (2015); Tay (2021)
Data-management plan	A document describing how the data will be handled during a project and what happens with the data after the project ends.	Michener (2015)
Data wrangling/munging	The process of transforming and mapping data from one “raw” data form into another format with the intent of making it more appropriate and valuable for a variety of downstream purposes, such as analytics.	Endel & Piringer (2015); Kandel et al. (2011)
Digital object identifier (DOI)	A number and letter string to identify and protect intellectual property in a digital environment.	Chandrakar (2006)
Early career researcher (ECR)	Individuals that are early in their academic career; typically from graduate or PhD student to postdoc level, sometimes even young principal investigators, such as junior professors.	Bazeley (2003); Laudel & Gläser (2008)
First author	The first author is the person listed first in an author list of a manuscript. In many fields, it is the person who has done most of the hands-on work and who has taken on a pivotal role in the research project. Shared co-first authorship is possible when two (or more) authors provided equal first-author-level contributions.	Riesenberg (1990)
Garden of forking paths/researcher degrees of freedom	Metaphor for the many (analytic) decisions that researchers can take, leading to many possible outcomes. The multitude of possible decisions can give rise to questionable measurement practices, such as p-hacking or hypothesizing after the results are known (HARKing).	Gelman & Loken (2013); Botvinik-Nezer et al. (2020)
Impact factor	A metric used to evaluate the relative importance of a scholarly journal in a particular field by measuring the average number of citations received per article published in that journal over a specific period of time. It is calculated by dividing the total number of citations a journal receives in a given year by the total number of articles published by the journal in the preceding 2 years. It is commonly used as a tool to assess the quality and significance of research, and has become an influential factor in the academic publishing industry, although it is controversially discussed.	Sharma et al. (2014)

(continued)

Table 1. *(continued)*

Term	Definition	References
Ivory tower	A metaphor for academia, portraying scientists as a group of closed-off individuals living in a tower and discussing scientific progress only among themselves, limiting the outreach of scientific results.	Bond & Paterson (2005); Lewis (2018)
Lab book	Also known as a laboratory notebook; a scientific recordkeeping tool used by researchers, scientists, and students to document their research project, experiments, observations, data, and findings.	Schnell (2015); Guerrero et al. (2019)
Open access	When scholarly content (e.g., software, data, materials, or output) is published in a way that is freely available to everybody.	Evans & Reimer (2009)
Operationalization	The process of rendering a theoretical construct concrete and tangible, thereby facilitating empirical observation and study.	Haucke et al. (2021)
Paywall	A digital barrier implemented by academic publishers restricting access to scholarly content (e.g., articles) to researchers or institutions that have paid for a subscription (or a one-time access). These costs are intended to cover processes associated with editing, peer reviewing, and formatting; however, paradoxically, they limit dissemination and potentially hinder scientific progress. Hence, some researchers advocate for open-access publishing models to promote equity in knowledge distribution.	Barbour (2006); Day et al. (2020)
Peer review	The act of giving feedback on a manuscript under consideration at a scientific journal. Typically, a minimum of two reviewers that are experts in the field are invited to comment on a manuscript. Subsequently, editors make a decision whether to accept or reject the submission, and authors can be asked to revise their work based on reviewers' comments.	Jana (2019)
Pilot study	A pilot study is a small-scale preliminary investigation that is conducted before a larger research project or study to test the feasibility of the research design, methods, and instruments. The primary purpose of a pilot study is to identify potential problems and areas for improvement in the research protocol that can be rectified before conducting the actual study.	Arain et al. (2010); In (2017); Thabane et al. (2010)
Postprint	The accepted or published version of a manuscript in a scientific journal. Postprints can often be shared on public repositories to make them accessible to everyone and forgo the paywall. Note that journal-specific policies (e.g., embargo periods) need to be considered.	Harnad (2003)
Power analysis	A statistical method used in research to determine the sample size needed for a study to achieve a desired level of statistical power. Statistical power refers to the ability of a study to detect a significant effect (or difference) between groups or conditions when a true effect (or difference) exists.	Kemal (2020)
Preprint	A version of a manuscript that has not yet been peer reviewed and published in a scientific journal but is uploaded to an open-access online repository, usually at the time of submission to a journal. Because preprints did not undergo the established scientific quality-control process (i.e., peer review), preprints usually include a brief note that the reported findings should be examined with caution by practitioners, journalists, and policymakers. Note that preprint servers can also include postprints.	Hoy (2020); Wingen et al. (2022)

(continued)

Table 1. *(continued)*

Term	Definition	References
Rebuttal	A written response to a criticism made against a research manuscript or proposal. It aims to refute or dispute opposing arguments by presenting counterevidence or alternative interpretations or theories. Thus, rebuttals are an important aspect of peer-review processes that allows for the improvement of scientific work through constructive feedback or critical discourse.	Palminteri (2023)
Registered report	A type of scholarly article format that involves a two-stage peer-review process. In this format, authors submit a detailed research proposal or protocol to a journal, which is then peer reviewed before any data are collected. If the proposal is deemed to be methodologically sound and potentially meaningful, the journal agrees in advance to publish the results of the study regardless of the outcome.	Henderson & Chambers (2022)
Revise and resubmit	An outcome resulting from the submission of a manuscript to a scientific journal. The manuscript is rejected in its current form, but the authors are invited to revise and resubmit their work after incorporating feedback from reviewers.	Kornfield (2019)
Reproducibility	The ability to successfully reproduce (parts of) experiments from other researchers in similar or different contexts, that is, coming to the same conclusions as the original researchers.	Pennington (2023)
Senior author	The senior author is the lead person (e.g., classically the principal investigator) primarily associated with funding, supervision, or major responsibility for the project. Shared co-senior authorship is possible when two (or more) authors provided equal senior-author-level contributions.	Pain (2021)
Standard operating procedure (SOP)	Documents or materials describing study procedures or processes for the purpose of establishing and managing data quality and reproducibility.	Manghani (2011)
Type I error rate	Type I or alpha error rate in statistics refers to the probability of rejecting a null hypothesis when it is actually true. In other words, it is the likelihood of obtaining a statistically significant result by chance alone, without any true underlying effect.	Banerjee et al. (2009)
Type II error rate	Type II or beta error rate in statistics refers to the probability of falsely rejecting the alternative hypothesis and maintaining the null hypothesis when the alternative hypothesis is actually true. Beta can be used in power analyses.	Hartgerink et al. (2017)
Work package	A major subpart of a research project with a specific and verifiable point (e.g., a fully programmed paradigm, an ethics approval, a dissemination item, or any other deliverable in the project).	Li & Hall (2019)

Note: The first occurrence of each term is in italics in the text. For a broader overview regarding open-science-related terms, please refer to the FORRT glossary (Parsons et al., 2022).

selected this framework because of the robust capabilities offered by GitHub for project management, development, and deployment within a single platform. In addition, GitHub Pages can host tools generated via JavaScript backend. We have exploited this feature to develop our network tool using a Cytoscape.js (Franz et al., 2016) backend. Furthermore, we have secured the backend by locally hosting the Cytoscape.js instance within our project's GitHub repository. This approach safeguards the project from potential disruptions caused by significant changes in the Cytoscape.js backend because we maintain our own copy of the Cytoscape.js instance.

Collaboration opportunities

There are multiple ways to contribute to the database and tool via buttons on the corresponding ARIADNE website https://igor-biodgps.github.io/ARIADNE/graph/graph.html. First, users can directly submit new resources to be added via a Google Form or a GitHub issue because this technique has proven useful for earlier

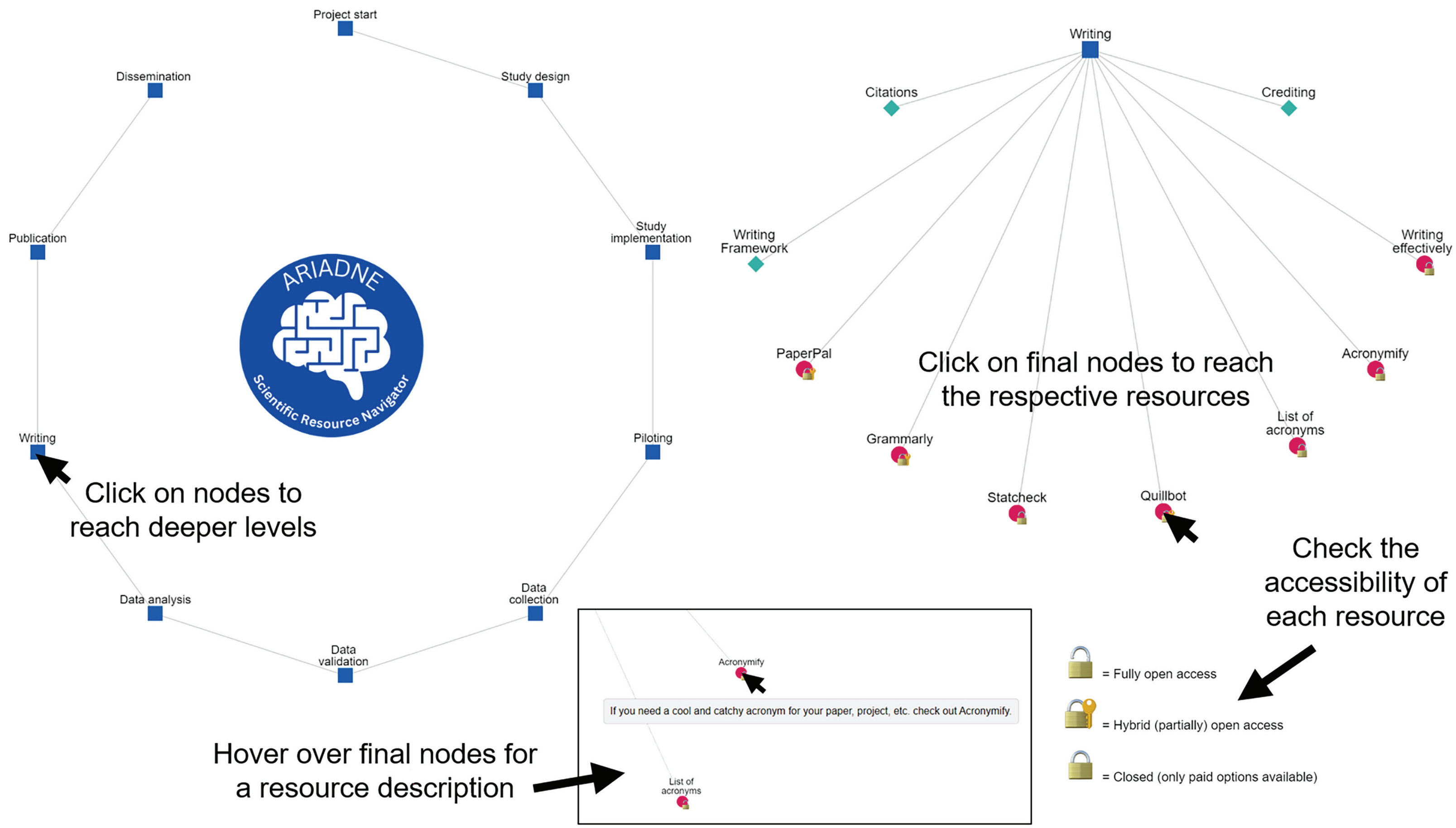

Fig. 1. Exemplary visualization of ARIADNE—a scientific resource navigator (ARIADNE website: https://igor-biodgps.github.io/ARIADNE/graph/graph.html). Clicking on nodes leads to deeper levels (black arrow keys). The final level shows all associated resources, including descriptions and hyperlinked websites (e.g., Project start → Writing → Quillbot). Lock icons indicate the accessibility of a certain resource.

versions of this tool (e.g., Hartmann, 2021). Because we have expected that not all future users are well versed with GitHub, each submitted Google Form will automatically create a unique issue in the GitHub repository. Once the issue is submitted, the ARIADNE Team will review the entries (e.g., regarding functionality of links and compatibility with the tool's framework) and, after approval, integrate them into the relevant subsection. Likewise, software bugs and other issues can be reported directly through GitHub or Google Forms to allow for version tracking. Therefore, we characterize our tool as a community-driven and open-source tool.

Long-term sustainability

Many community-driven projects suffer when core members driving the initial effort turn to other projects or leave science altogether. We have therefore put special emphasis on the sustainability of ARIADNE. ARIADNE is supported institutionally by the Leibniz Institute for Psychology, which is a research institute with long-term funding from the renowned Leibniz Gemeinschaft for infrastructures to support psychological science in Europe (https://leibniz-psychology.org/en). ARIADNE was initiated by and is sustained by the Interest Group for Open and Reproducible Science of the section Biological Psychology and Neuropsychology (https://www.dgps.de/fachgruppen/fgbi/aktivitaeten-der-fachgruppe/igor), which forms part of the German Psychological Society and currently consists of 100+ members conducting active projects (e.g., Nebe et al., 2023). ARIADNE is thus embedded in institutional and community structures of psychology in Germany, which will aid with long-term availability and scaling plans going forward. In the future, we hope to attract support also from international partners championing open-science initiatives. To ensure the long-term viability of ARIADNE, we have established a dedicated team (authors of this article and future contributors) responsible for regular updates and reviews of the resource database. We actively encourage community contributions through Google Forms and GitHub issues, allowing researchers to submit new resources and report issues. By fostering a collaborative environment, we aim to create a dynamic and evolving resource that meets the needs of the research community.

The tutorial

In the following tutorial, we guide researchers through a standard research project in psychological science facilitated by ARIADNE. We divide the research cycle into 10 steps that determine the quality and the success of research projects. We describe the challenges and choices to be made in each step and provide curated resources from ARIADNE for each of them: (1) project start, (2) study design, (3) study implementation, (4) piloting, (5) data collection, (6) data validation, (7) data analysis, (8) writing, (9) publication, and (10) dissemination. We also introduce key terms relevant in each step to facilitate training and communication between experienced and new academics (see Table 1 and italicized words in the main text). Finally, we provide a checklist with questions one might ask at each step of a research project in Table 2. Please keep in mind that some of these questions may be relevant before starting a certain step.

Step 1: Project Start

Research question

Even before the start of a project, researchers already have to make a variety of decisions. Most important is the formulation of an interesting research question, which can be done based on past work or an observation in one's own data. Here, researchers also need to decide if their question warrants an original or replication study design. Critically, a research gap or limitation of previous work can be derived from published and unpublished literature (Pautasso, 2013).

Literature search

Defining the gap may require a comprehensive and systematic literature search using subject-specific databases and search engines (e.g., ➜ PsycInfo, American Psychological Association [APA]; ➜ PubMed, National Institutes of Health). However, because novel research findings that are still in the *peer-review* process cannot be found via these databases, researchers should also widen their search toward *preprint* repositories (e.g., ➜ MetaArXiv, ➜ bioRxiv, ➜ PsyArXiv, or ➜ PsychArchives) for appropriate content, keeping in mind that the latter work may not have undergone peer review yet. Typically, preprint servers add a note to the manuscripts that have already been published. In addition, linking identified articles to maintain an overview of their interrelationships is essential for tracking and comprehending the compiled scientific literature (e.g., ➜ Connected Papers or ➜ Research Rabbit).

Hypothesis and research design

The more data on a question already exist and the more rigorous these data have been collected and analyzed, the more likely it may be that a research question can be derived for which hypotheses can be operationalized that will be supported by the new data to be collected. However, this enhanced likelihood may come at the expense of novelty, that is, if the probability of support for the hypothesis is 100% (or close), there is no point in running the experiment. Currently, psychological

Table 2. Checklist of Relevant Questions for Each Step of the Research Cycle

Step	Questions
1. Project start	What is the gap in the literature and the resulting research question?[a] Is funding available to conduct the project?[a] What are the time plan and work packages of the project?[a] Who is responsible for what in the project?[a]
2. Study design	What are the hypotheses and how can they be tested? Which independent variables are manipulated? Which dependent variables need to be measured? Is approval by an ethics/institutional review board needed? How large should the sample be?
3. Study implementation	What measures are most fitting (tasks, questionnaires, etc.)? What stimuli need to be created (e.g., pictures, videos, text)? Which programming environment should be used?
4. Piloting	Is the study feasible?[a] Do all manipulations work as intended?
5. Data collection	How can we make sure the data are safely stored, accessible, and backed up?[a] Are the data collected in a way that protects private and sensitive information (e.g., of participants)?[a]
6. Data validation	How can we ensure the quality and accuracy of the data?[a] How can we store the data reproducibly?[a]
7. Data analysis	What are specific analysis pipelines and programs that can be used for specific types of data (e.g., EEG, functional MRI, behavior)? Which open-source software is a good alternative to proprietary products?[a] Which tools allow complete replicability of an analysis pipeline, independent of the specific operating system of a user or continuous software updates? How are results visualized in a captivating yet transparent and maximally inclusive way?
8. Writing the manuscript	What is the scope of the manuscript? What is the target audience and journal? How to write a convincing abstract? How to properly credit authors? How to find and cite sources correctly? How to structure a manuscript? Which frameworks allow to conveniently write a reproducible manuscript?
9. Publication	Where to upload data, code, materials, and/or a preprint?[a] Are the published data FAIR ("Findable, Accessible, Interoperable, and Reusable")?[a] How to write a cover letter? How to write a rebuttal to reviewer comments?
10. Dissemination	How to design a poster for a conference? How to prepare a scientific presentation? How to present the research to a lay audience?

[a]These questions should ideally already be explored before starting a project.

science, in almost all cases, cannot support such a high a priori probability, and thus, direct or conceptual replications of prior work have been highlighted to be critical to scientific progress (Nosek & Errington, 2017; Röseler et al., 2024).

Funding and feasibility

Depending on the research question, different amounts of funding are required, so a third-party funding application might be necessary. Researchers who depend on grants have to keep in mind that such applications take substantial amounts of time and are not guaranteed to succeed. If there is not enough money available, it may be an option to adapt the research question accordingly at this stage (e.g., switching from a lab experiment to an online experiment). Researchers can also first conduct a *pilot study* for feasibility testing and use the obtained results for a funding application (see Step 4). One should also consider whether the research question can be answered in the time available, in particular, in the case of fixed-term contracts.

Teamwork

Researchers who work on a joint research project have to discuss (and document) the responsibilities of each member of the project team. Possibly, during the following steps, the research group may realize that further expertise is required, which can lead to the inclusion of additional coauthors. Finally, the research group should establish a workflow pipeline together that outlines the subsequent steps (i.e., Steps 2–9; Gantt charts: bar charts used to illustrate a project schedule, showing start and finish dates of activities, responsibilities, and their dependencies ➜ Ganttrify). This is particularly useful for a set of related tasks within a project (e.g., planning, scheduling, and monitoring projects and *work packages*). ARIADNE thus also features many resources surrounding time planning and project organization. Moreover, our tool highlights the role of communities and *big team science* (see Table 1) by providing examples of organizations and groups that conduct large-scale research together across the globe.

Step 2: Study Design

Conceptualization

In an empirical research project, the study design encompasses conceptualizing and planning the methodology for data collection and analysis, including the development of a study protocol, how to operationalize the research question and variables, and planning the next steps regarding data collection, analysis, and interpretation (Steps 5–8). In other words, the study-design step lays out the foundation for the entire project and provides a roadmap for all subsequent steps. It is essential for the study design to be well conceived, well executed, and well documented to ensure the quality, integrity, and generalizability of the findings of the research.

Documentation and flexibility

Documenting the decision-making process throughout the research project and creating a detailed data-collection protocol are crucial for enhancing *reproducibility*, enabling other researchers to understand and replicate the study with greater ease. It is essential to maintain flexibility in this step, allowing for adjustments as long as the project is still being planned. After all major methodological and analytical decisions have been made, it is advantageous to consider adopting an open-science approach to be transparent (e.g., a preregistration or *registered report* documents one's original ideas with a timestamp; Haroz, 2022; Laine, 2017).

Sample size and power

Another important aspect of the study-design step is determining the appropriate sample size, target population (e.g., neurotypical individuals or patients), and the sampling strategy (e.g., stratified or convenience sampling; Stratton, 2021). To ensure that the study has sufficient statistical power to detect meaningful differences or associations, justification of one's sample size is helpful at this stage, for example, via a *power analysis* (➜ G*Power, ➜ Sample Size Justification Shinyapp; Cohen, 1962; Jones, 2003; Kemal, 2020; see Table 1) or funding constraints.

Ethical considerations and approvals

In this step and for most psychological empirical research projects, approval by the local ethics committee or an institutional review board should be applied for. Considering ethics in experimental design involves taking steps to protect the rights and welfare of participants, weighing costs and benefits while minimizing risks, ensuring the privacy of participants and the confidentiality of their data, but also obtaining approval for sharing data as openly as possible. It also involves considering the impact of the findings on society and potential biases that may exist in the study.

Data structure and management

Determining the data structure and arrangement enhances the accessibility and organization of the collected data. For example, complex neuroimaging, EEG, or eye-tracking data can be organized using the ➜ Brain Imaging Data Structure (BIDS; Gorgolewski et al., 2017; see also Step 5). First thoughts regarding a data-management plan should already be done now.

Collaboration and expertise

Drawing on the experience from supervisors, mentors, and/or collaborators is key in this step because they might have specific expertise or experience with certain aspects of the planned project. In this and the previous step, the role of communities and collaboration with others for the sharing of knowledge and expertise becomes especially clear (e.g., in "Big Team Science" projects; for primers and tutorials, see Step 1 and Baumgartner et al., 2023; Forscher et al., 2023; Hall et al., 2018).

Authorship

Criteria, tasks, and rules for (co)authorship should be discussed already at an early stage of the project and rediscussed over its course if changes arise (➜ *CRediT statement*; Brand et al., 2015; Tay, 2021; see Table 1 and Step 8).

Step 3: Study Implementation

In contrast to Step 2, which focuses on planning the research project, Step 3, study implementation, involves translating those plans into action. It entails developing tasks or paradigms to manipulate independent variables and measure dependent variables and creating necessary stimuli and control conditions. Whereas Step 2 sets the theoretical and methodological framework, study implementation (Step 3) addresses the practical execution, including the precise crafting of stimuli and control over experimental conditions. This phase ensures the smooth transition from theory to practice, focusing on the creation of tasks, stimuli, and control conditions to achieve the research objectives outlined in the study design.

Stimuli selection and standardization

The selection of openly available stimuli on platforms such as the ➜ Kapodi Stimuli database or ➜ International Affective Picture System is recommended to not only enhance reproducibility but also ensure the use of stimuli that underwent a proper standardization procedure (Lang et al., 2008). Note that, crucially, the trap of "questionable measurement practices" as indicated by Flake and Fried (2020) should be avoided by favoring materials that have been tested for standardization, reliability, and validity (e.g., stimuli, tasks, questionnaires; ➜ APA PsycTests or ➜ Open Test Archive). However, researchers should consider that task reliability can mean different things in experimental and correlational research (Hedge et al., 2018; Nebe et al., 2023).

Developing procedures and protocols

Other aspects of study implementation may include the development of a *standard operating procedure* (SOP; Manghani, 2011; see Table 1) or protocol to guide the experimenter through the study, the creation of a data-collection and -analysis plan, and the implementation of procedures to ensure the reliability and validity of the study (see also Step 6). It is immensely helpful to note down decisions and the reasons for these decisions because those will be relevant for the later writing process (Step 8). For example, the decision for a suitable task-programming environment should take into account whether the study will be lab-based or implemented online and whether the program is available at no costs (➜ Psychopy vs. ➜ Psychtoolbox in Matlab).

Preregistration and Registered Reports

In this context, preregistration, which entails documenting and uploading the research plan before the outset of data collection, including the hypothesis, design, and analysis plan, can be employed as a crucial tool in transparent and reproducible scientific research (Toth et al., 2021; ➜ PROSPERO for systematic reviews, ➜ OSF templates, or ➜ PreReg). This practice helps to prevent an inflation of the false-positive rate (see "*Type I error*" in Table 1) by reducing *researcher degrees of freedom* and/or limiting decisions within the *garden of forking paths* (see Table 1). Furthermore, it improves transparency and reproducibility of the study (Peikert et al., 2021). An extension of preregistration, so-called registered reports (Henderson & Chambers, 2022), even shifts the peer-review process from after to before data collection, allowing researchers to get feedback on their work early in the process and to be able to adapt their research design before the study starts (Scheel et al., 2021).

Step 4: Piloting

A pilot study, also known as exploratory trial, is a preliminary small-scale study conducted to assess potential problems, duration, and other factors before a full experimental investigation. This is often a reflective and iterative process (Thabane et al., 2010). By setting criteria based on important feasibility objectives and research goals, researchers can use pilot studies to determine the feasibility of a more extensive, time-consuming, and expensive main study and to test whether the *operationalization* (Step 2) makes sense (see ARIADNE for resources related to piloting; e.g., ➜ data simulation). Note that certain study types, such as literature reviews, might not need a pilot study but instead require piloting in the sense of testing the search criteria and procedures.

Feasibility

It is common to always test a few "pilot" participants with your whole setup before starting Step 5 (the data collection), making sure that participants understand the instructions of the experiment and all procedures work as planned. The main study can then be improved based on the findings of this pilot. Another complementary method for better determining a study's feasibility is to simulate data, which allows researchers to set up and test the analysis pipeline and prepare for prospective outcomes before carrying out the primary investigation.

Validation

In addition, on an operationalization level, these preliminary data should be used to check whether all variables of interest can be extracted from the raw files. Note here that data from pilot studies or participants should ideally be kept separate from the data of the main study because they might differ in the way they were measured. Although preliminary data from pilot studies can be used to estimate effect sizes for sample-size calculations of the main study (Sakaluk, 2016), these estimates might be inaccurate because of the small-scale nature of the pilot (Albers & Lakens, 2018). In the worst case, the sample-size calculation is based on overestimated effect sizes, leading to the initiation of an underpowered main study that is susceptible to false-positive (Type I error) or false-negative (*Type II error*) findings. Sample-size calculations from pilot studies should therefore be treated with caution (Lakens, 2022).

In conclusion, piloting can be useful for study planning and design, enabling researchers to evaluate viability, foster greater transparency, and enhance the overall quality of their research.

Step 5: Data Collection

Before starting with data collection, researchers can create a standardized manual (SOP; see Step 3 and Table 1; Manghani, 2011) and document the experimental procedure in a *lab book* (Schnell, 2015) that lists unforeseen events and information for each participant/session. The latter ensures that important details, such as equipment malfunctioning, reasons for participant dropout, noticeable participant behavior, and any crucial decisions or modifications made on the fly, are not lost or forgotten. Crucially, a lab book can and should be used in all kinds of studies, whether they are online or lab-based, to clearly document any issues, methodological decisions, and changes to the protocol. Note that writing up the methods section during Step 5 promises to save time prospectively and enhances the precision and reproducibility of the research project. Here, data-management strategies from previous steps, such as intuitive data-saving structures, can help to avoid misunderstandings and waste of time because of data rearrangement or script rewriting (Michener, 2015). Having all data regularly backed up during data collection is essential to prevent valuable data from being accidentally lost. These practices later facilitate data, code, and material sharing as part of the publication (Step 9; Contaxis et al., 2022). Ideally, decisions regarding the data-management structure are already made in Step 2. Even though the scientific community still lacks consensus on data-arrangement structures and is constantly finding new approaches, there are already well-established structures, such as BIDS. Furthermore, data anonymization or pseudonymization are critical techniques to protect participants' rights and privacy (for ethical data sharing, see Meyer, 2018; for European Union regulations on data privacy, see Hallinan et al., 2023).

Step 6: Data Validation

Data validation in a research project refers to the process of ensuring the quality and accuracy of the data collected during the study (e.g., for machine-learning projects, see Breck et al., 2019). This step starts already during study design (Step 2) and should be continuously revisited throughout the data collection.

Data quality

Accordingly, quality control refers to the continuous process of evaluating the data or procedures, such as SOPs, for completeness, accuracy, and consistency and identifying and removing any errors (Freire, 2021). This may include checks for missing data, incorrect data entry, or other issues that could affect the validity of the study and subsequent interpretation of the results but also includes assuring your data are FAIR ("Findable, Accessible, Interoperable, and Reusable"; Wilkinson et al., 2016; ➜ FAIR data or ➜ RDMkit).

Data accuracy

Data wrangling, also known as *data munging*, is the process of transforming and mapping data from one "raw" data format into another format with the intent of making it more appropriate and valuable for a variety of downstream purposes, such as analytics (see Table 1; Endel & Piringer, 2015; Kandel et al., 2011). This step has the ultimate goal of cleaning, organizing, documenting, and preserving the data for future use. This may include creating detailed metadata, documenting the data-collection and data-cleaning process, and storing the raw and processed data in a secure and accessible format (which might mean that the software and version used to gather and process data has to be stored as well). However, aspects such as data quality, merging data from different sources, creating reproducible processes, and data provenance are equally important. Regarding preprocessing of data, many fields already offer established standards (e.g., for reaction-time data, see Loenneker et al., 2024).

In sum, this step contributes essentially to the replicability of the study's findings and the ability to build on the research in future studies. This step can be started as soon as first (pilot) data are collected, leading to the next step, data analysis.

Step 7: Data Analysis

Commonly, this step overlaps with Step 6. Initial data analysis refers to the process of data inspection and reorganization that needs to be carried out before formal statistical analyses (Huebner et al., 2016). This process includes metadata setup, data cleaning/screening/refining, updating the research-analysis plan, version control, and the documentation of initial data-analysis procedures (see Baillie et al., 2022). Ideally, the data-analysis procedure for the current project has been thoroughly planned and fixed in advance during Step 3. But even then, many new decisions have to be made at this stage, which may affect the next steps, such as how the data can be best shared with others, how they allow for collaborative data analysis, or how results are best visualized (Kroon et al., 2022).

Choosing the right analysis framework one feels comfortable with is just one of the many challenges in this step (➜ RStudio, ➜ JASP, and ➜ Jupyter Notebook). If the study was not preregistered, statistical approaches that are suitable for the research question need to be chosen (e.g., Bayesian vs. frequentist statistics; Pek & Van Zandt, 2020; van Zyl, 2018). If applicable, correction methods for multiple comparisons should be considered (Alberton et al., 2020; Noble, 2009) to avoid a potential increase in Type I error rate (see Table 1). Crucially, in recent times, there has been a shift in the focus of group-level to individual-trajectory analyses, which has a significant impact on the required sample size and the effect size (Marek et al., 2022).

To overcome inherent inaccuracies associated with estimating effect sizes, sequential analyses involve monitoring data collection as it progresses and controlling for Type I error rate (Lakens, 2014). During sequential analyses, at a predetermined stage in the project (e.g., defined in Step 2), an interim analysis can be conducted to determine whether the collected data provide sufficient evidence to conclude that an effect is present, whether more data should be gathered, or whether the study should be terminated if the predicted effect is unlikely to be observed (Lakens, 2014). This analysis approach should ideally also be preregistered. Note that data analysis is a critical step that has attracted much attention recently in light of the so-called “replicability crisis” (Anvari & Lakens, 2018) because this is a stage with high researcher degrees of freedom, during which questionable research practices (John et al., 2012) and biases may occur (even inadvertently; for improving the data extraction in meta-analyses, see e.g., Ivimey-Cook et al., 2023).

Finally, in the process of analyzing results, it is also essential to consider the role of visualizations. Effective visual representations can enhance the comprehension of complex data sets and findings (➜ BioRender, ➜ Mermaid, or ➜ Nipype).

Step 8: Writing the Manuscript

Once data are analyzed and discussed with supervisors and potential coauthors, researchers are set to outline their results in a comprehensive manuscript (Mensh & Kording, 2017).

Target journal

The decision for a target journal is usually made together with the project team (i.e., supervisor, collaborators, and coauthors; see also Step 1; ➜ Journal/Author Name Estimator). The choice of journal should be influenced by the article. However, this can mean a broader disciplinary journal, a more specific topic-related journal, a methodological journal, or a more generalist journal. Various criteria can guide the journal selection (Salinas & Munch, 2015). Criteria such as *impact factor* (see Table 1) and journal prestige may be critical for more senior researchers, who need to build up a reputation, whereas acceptance rates and turnaround times may be more important for ECRs, who need to complete their degree within a limited amount of time. It is also important to consider open-science policies, practices, and procedures of the respective journal or publisher when choosing a journal. For example, the journal choice could be influenced by moral (not wanting to support certain publishers; see Smith et al., 2023) or logistical reasons (opting to publish in an open-access journal with payable *article processing charges*). Moreover, journal choice will directly affect how the article can be accessed (e.g., open access or *paywall*) and whether and how preprints and *postprints* can be shared with the scientific community (see Table 1).

Manuscript structure

A journal will often specify the manuscript sections to be included, how many words to write, how many figures or tables to include, and whether there is space for supplementary materials. For example, writing a manuscript with the results directly after the introduction as opposed to after the methods will substantially change the way the whole manuscript needs to be organized.

Authorship

Authorship of the manuscript should be offered to individuals who agree to make substantial scientific contributions to the project (see e.g., APA Ethics Code Standard 8.12a, https://www.apa.org/ethics/code; see also Step 1). These include but are not limited to conceptualization, data collection, data analysis, writing, funding, or supervision. However, the status of authorship positions varies strongly depending on the scientific discipline (Pain, 2021). In human neuroscience, for example, the order of authorship usually reflects the relative contributions of the researchers involved (e.g., ➜ Credit Author Statement and ➜ Tenzing). Whereas the *first author* is typically the person who has contributed most to the project (e.g., the graduate student), the person who is supervising the project often appears last (*senior author*; see Table 1; Pain, 2021). The other authors are named in between, usually in descending order of decreasing contributions. The *corresponding author* is usually the person who takes primary responsibility for communication regarding the manuscript, which may, for example, be the first or last author. Other fields may opt to include people with minor contributions or choose an alphabetical/random author order (Pain, 2021).

Finally, before the manuscript continues along its route to publication, the authors should make sure that the manuscript is error-free and the data in it are reproducible (e.g., ➜ StatCheck or ➜ Papaja).

Step 9: Publication

There are many ways in which to disseminate scientific work (Bourne, 2005; see Step 10), and some of these are summarized in ARIADNE.

Preprints

Preprints facilitate early access to the manuscript, which helps researchers to document their scientific work and may even be used to assert priority (e.g., ➜ MetaArXiv, ➜ bioRxiv, ➜ PsyArXiv, or ➜ PsychArchives; Bourne et al., 2017). Preprint publication often happens simultaneously with the submission to the target journal. Some have suggested that the accessibility and reception of a manuscript may make it easier to assess the quality of scientific work than bold claims about the novelty or impact of the work (e.g., in scholar-governed information infrastructures as opposed to legacy journals; Brembs, 2019). However, be aware that some journals still prohibit the upload of all or specific manuscript versions as preprints (➜ Sherpa Romeo).

Journal submission

Most journals ask researchers to submit the manuscript together with a *cover letter* (see Table 1). The cover letter allows researchers to demonstrate the relevance and quality of their work. However, some journals actively discourage the submission of a cover letter to let the manuscript "speak for itself."

Peer review

Once the manuscript is under peer review, reviewers might raise more or less critical issues about the manuscript and inform the editor handling your paper (Suls & Martin, 2009). In this context, fellow researchers provide comments that may be useful for a critical reevaluation of the manuscript. The editor then recommends either acceptance, minor revisions (both rarely happen on the first submission), major revisions, *revise and resubmit* (see Table 1), or rejection. Note that these terms and their meaning may vary from journal to journal (e.g., "reject" might sometimes indicate an option to resubmit a revised version and sometimes not). Some journals (e.g., Collabra, https://help.scholasticahq.com/article/134-what-does-the-manuscript-status-mean) include a page with the meaning of these different statuses. Addressing each issue raised by the reviewers in a well-crafted, point-by-point response *rebuttal* letter (Palminteri, 2023; see Table 1) allows researchers to demonstrate that criticized parts of the manuscript have been revised to an extent that warrants the acceptance of the manuscript (Noble, 2017) or argue why suggested changes have not been implemented.

Open code, data, and materials

Following acceptance, researchers may think about publishing their data and code together with the manuscript in a way that allows easy access to and reuse of the work (Goodman et al., 2014). Ultimately, sharing open code, data, and materials with licenses is highly favorable considering the rise in open-science practices (Contaxis et al., 2022). However, a server's privacy policies and the respective lawful basis (e.g., General Data Protection Regulation; Houtkoop et al., 2018; Peloquin et al., 2020) should be carefully considered when choosing a platform (➜ OSF, ➜ Zenodo, or ➜ PsychArchives). Published products can be assigned their own *digital object identifiers* and constitute important research outputs next to published manuscripts (e.g., in modular publishing using ➜ Octopus or ➜ ResearchEquals).

Publication

This process until seeing your manuscript published can take several months (in rare cases, even years), and this time should be factored in Step 1, during which a time plan of the project is first established. If your manuscript is rejected by your first journal choice, a submission to an alternative journal is usually warranted. An appeal (i.e., contesting the rejection) can be considered only in exceptional cases. Crucially, if you notice an error only after publication (e.g., a software bug or faulty code/input data), this should be discussed with the coauthors and corrected in the published article as soon as possible (Bruns et al., 2019).

Step 10: Dissemination

Once a study has been preprinted and/or published, the dissemination process does not necessarily end

(Bourne, 2007). It can be important to pursue additional dissemination strategies to reach as many people as possible to benefit from the new findings (Ross-Hellauer et al., 2020). Generally, two target groups should be differentiated when it comes to dissemination: academic and non-academic audiences.

Academic audiences

Typically, new findings are presented at conferences in the form of talks or posters (Pain, 2022) and circulated on social media platforms (e.g., ➜ Bluesky or ➜ Mastodon). These dissemination forms might happen before or during Step 9 as part of the preprint upload or even as early as Step 7 to get peer feedback on the freshly analyzed results.

Nonacademic audiences

Regarding reaching the general public, science communication journals can also be addressed (➜ In-Mind, ➜ Scientific American, ➜ APS Observer, ➜ APA Monitor on Psychology, or ➜ Gehirn und Geist), and usually the outreach offices of many institutions can be contacted to circulate a press release among regional and national news outlets.

A wide-reach dissemination strategy is highly recommended because research has increased value beyond the academic community when a study's findings leave the academic *ivory tower* (see Table 1) and are communicated to the general public and stakeholders, such as funders.

Discussion and Outlook

With this comprehensive overview of the 10 most important steps of a psychological research project and their inherent respective challenges, we present our tool ARIADNE as a tool to support the research process. By explicitly highlighting open-access resources, we level the playing field for researchers from underprivileged countries or institutions. We also facilitate good practice through open, fair, and reproducible research methods in psychology and empower researchers of all career stages to conduct their research projects with the help of this living and dynamic open-resource platform.

Providing an accessible and structured overview of high-quality resources is of utmost importance, particularly because institutions, funding agencies, and other stakeholders are putting in efforts to improve scientific quality (see e.g., the ➜ Declaration on Research Assessment). Improving research quality through collections such as ARIADNE will thus be an important contribution to kickstart and advance the careers of ECRs. Beyond ECRs, we hope that our tool can be widely distributed to researchers of all levels starting a new project, including supervisors sharing it with their employees. We also actively call on experienced researchers from all fields of psychological science to contribute their own tried-and-tested tools to our database. ARIADNE contributes to the seamless sharing of resources and guidelines, streamlining research workflows across the globe. In addition, the integration of open-source technological innovations, exemplified by the ARIADNE project, marks a pivotal advancement in psychological-research methodologies. This initiative is part of a broader movement toward digital solutions that facilitate comprehensive and reproducible science (see e.g., the ARTEM-IS project [Agreed Reporting Template for EEG Methodology - International Standard for documenting studies on event-related potentials]; web app: https://artemis.incf.org; Šoškić et al., 2023). The principles at the heart of ARIADNE—openness, reproducibility, and collaboration—are echoed in ARTEM-IS's approach, emphasizing the critical role of standardized practices in advancing the field. Other grassroots researcher communities and initiatives, such as Chinese Open Science Network (Jin et al., 2023; see also the list of scholarly and topical communities in ARIADNE), can amplify the reach and impact of tools such as ours. This unified approach underscores a commitment to an open and accessible scientific community and demonstrates how technological innovations are instrumental in shaping a future in which psychological research is more transparent, efficient, and inclusive.

Finally, we discuss a few limitations associated with ARIADNE. First, the resources provided in ARIADNE serve as curated recommendations from the scientific community. As a team of 10 researchers at different career levels, including PhD students, postdocs, and professors, we bring extensive experience and knowledge in using many of these resources. The resources provided in this article and in ARIADNE serve as curated recommendations based on current research practices. However, it is important for researchers to consider their own preferences and requirements when choosing resources for their experiments. Although we cannot guarantee the effectiveness, suitability, or long-term availability of any individual resource, we regularly update and add resources with a dynamic, quality-driven approach. Researchers are nevertheless encouraged to exercise their own judgment and discretion when selecting resources and conducting experiments.

Second, we want to mention a few challenges when creating ARIADNE because these insights may be valuable for users. Key issues involved determining the most effective and sustainable way to present resources (e.g., lists vs. nodes), navigating the variability in individuals' understanding of a typical research workflow (e.g., which resource belongs in which step), and establishing clear exclusion criteria to define what constitutes an ARIADNE resource and is included in the tool (i.e., avoiding nonpermanent links).

Third, we stress that although we have provided a comprehensive selection of key tools and resources, including all possible tools in this article would be impractical. Instead, the present version of ARIADNE is a starting point (i.e., not static but continually evolves as new tools are added). We actively encourage other researchers to add tools from their fields or replicate our methods, code, and infrastructure to create field-specific tools. This process ensures that the resource remains up-to-date and relevant, accommodating the latest developments in research tools and methodologies. Hence, future versions will include resources and information regarding supervision and mentoring (Jabre et al., 2021); academia beyond the PhD (postdoc level: Bourne & Friedberg, 2006; professor level: Tregoning & McDermott, 2020); lab life (Maestre, 2019); building up collaborations, networking, and lab exchanges (Vicens & Bourne, 2007); how to deal with article rejection ("How [Not] to Appeal," 2021); and time management, progress tracking, and grant writing (Bourne & Chalupa, 2006).

In conclusion, we believe that this resource encourages not only ECRs but also more senior researchers to delve into new research projects using our tool as a starting point. ARIADNE alleviates the challenges attached to starting out in science; prevents a constant, frustrating "reinvention of the wheel"; and provides helpful support during all stages of the research cycle—for everyone.

Transparency

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Author Contributions

H. Hartmann and Ç. Gürsoy are shared first authors. A. Kastrinogiannis and A. Koppold are shared last authors.

Helena Hartmann: Conceptualization; Data curation; Investigation; Methodology; Project administration; Supervision; Validation; Visualization; Writing – original draft; Writing – review & editing.

Çağatay Gürsoy: Conceptualization; Data curation; Investigation; Methodology; Project administration; Software; Supervision; Validation; Visualization; Writing – review & editing.

Alexander Lischke: Conceptualization; Data curation; Investigation; Methodology; Validation; Writing – original draft; Writing – review & editing.

Marie Mueckstein: Conceptualization; Data curation; Investigation; Methodology; Software; Validation; Visualization; Writing – review & editing.

Matthias F. J. Sperl: Conceptualization; Data curation; Investigation; Methodology; Validation; Writing – original draft; Writing – review & editing.

Susanne Vogel: Conceptualization; Data curation; Investigation; Methodology; Validation; Writing – original draft; Writing – review & editing.

Yu-Fang Yang: Conceptualization; Data curation; Investigation; Methodology; Validation; Writing – original draft; Writing – review & editing.

Gordon B. Feld: Conceptualization; Data curation; Investigation; Methodology; Validation; Writing – review & editing.

Alexandros Kastrinogiannis: Conceptualization; Data curation; Investigation; Methodology; Software; Validation; Visualization; Writing – review & editing.

Alina Koppold: Conceptualization; Data curation; Investigation; Methodology; Validation; Writing – original draft; Writing – review & editing.

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Open Practices

This article has received the badge for Open Materials. More information about the Open Practices badges can be found at http://www.psychologicalscience.org/publications/badges.

ORCID IDs

Helena Hartmann https://orcid.org/0000-0002-1331-6683
Çağatay Gürsoy https://orcid.org/0000-0001-9762-7747
Alexander Lischke https://orcid.org/0000-0002-8322-2287
Marie Mueckstein https://orcid.org/0000-0002-7113-0879
Matthias F. J. Sperl https://orcid.org/0000-0002-5011-0780
Susanne Vogel https://orcid.org/0000-0001-9717-5568
Yu-Fang Yang https://orcid.org/0000-0001-9089-6020
Gordon B. Feld https://orcid.org/0000-0002-1238-9493
Alina Koppold https://orcid.org/0000-0002-3164-3389

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