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ARIADNE – a scientific navigator to find your way through the resource labyrinth

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Abstract

Performing high-quality research is a challenging endeavor, especially for early career researchers (ECRs). Most research is characterized by an experiential learning approach, which can be time-consuming, error-prone, and frustrating. While most institutions provide a selection of resources to help researchers with their research 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 early career researchers and their supervisors 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. The open-access database covers a constantly growing list of resources that are useful for each step of a research project, ranging from the planning and designing of study, over the collection and analysis of the data, to the writing and disseminating of findings. By introducing ARIADNE to the research community, we provide 1) a step-by-step guide on how to perform a research project, 2) an overview on resources that are useful at the different steps of such a project, and 3) a glossary of most common terms surrounding the research cycle. By focusing on open-access and open-source resources, we level the playing field for researchers from underprivileged countries or institutions, thereby facilitating open, fair, and reproducible research in the field of neuroscience.

Introduction

A comparison between research projects conducted two decades ago and those of today reveals a marked increase in the demands placed upon *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 pre-registration or dissemination possibilities (Ross-Hellauer et al., 2020; Tripathy et al., 2017), and the growing utilization of advanced computational and statistical techniques (Bolt et al., 2021; Bzdok et al., 2017) such as machine learning, as well as the implementation of 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 the first year of their work is more and more often accompanied by feelings of being overwhelmed (Kismihók et al., 2022; Levecque et al., 2017), as many project choices have to be made and a variety of skills need to be learned that determine the long-term success of one's first research project.

At this stage, most ECRs lack the necessary expertise and experience to make these important decisions. Moreover, many common terms need to be understood and learned. Learning this 'language of science' can be difficult for ECRs (Parsons et al., 2022; see also Table 1). In addition, institutions and supervisors often provide researchers with a relatively fixed array of available resources which are conventionally used, such as software subscriptions or in-house software. These tools are often expensive and bound to the institution itself (i.e., may become unavailable when the researcher changes institutions or works from home). On top of that, limited (subscription-based) resources might not only impede, but also prevent good scientific practice. Accordingly, many open access tools have been proposed to facilitate life as an ECR. However, these resources are often spread out and hard to find or to compare with each other in terms of reliability, validity, usability, and practicality. Moreover, these resources can be difficult to learn, in particular if there is limited support by supervisors. Taken together, these difficulties are 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 achieved.

Table 1

Mini glossary of science-related terminology, sorted alphabetically. The first occurrence of each term is highlighted in the text.

Term	Definition	References
Corresponding author	The corresponding author is typically the researcher who takes primary responsibility for communication regarding the manuscript, during both pre-publication and post-publication phases. This usually includes communication with the publisher, 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. It outlines the importance of the study and summarizes key findings and contributions to the field. Some journals explicitly require such a letter, while 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 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)
Early career researcher	An individual that is 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	Metaphor for the many (analytic) decisions that	Gelman &

Forking Paths / Researcher degrees of freedom	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).	Loken (2013); Botvinik-Nezer et al. (2020)
h-factor	A controversially discussed metric proposed by Hirsch (2005) to assess a researcher's (or journal's) scientific output by combining publication quantity and impact (i.e., citations). *h* is defined as the highest number of papers of an individual (or journal) with at least *h* citations (e.g., $h = 3$ means having 3 papers with at least 3 citations each).	Hirsch (2005)
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 two years and 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)
Ivory tower	A metaphor for academia, portraying scientists as a group of closed-off individuals living in a tower and discussing scientific progress only amongst themselves, limiting the outreach of scientific results.	Bond & Paterson (2005); Lewis (2018)
Lab book	Also known as a laboratory notebook, is a scientific record-keeping 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 (such as software, data, materials, or output) is published in a way that is freely available to everybody.	Evans & Reimer (2009)
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 et al. (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.	Jana (2019)

	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.	
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, which 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. Crucially, if a study is underpowered (i.e., the sample size is too small), researchers may not be able to detect significant effects even if they are present. Conversely, if a study is overpowered (i.e., the sample size is too large), resources may be wasted and the study may be unnecessarily expensive or time-consuming.	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. Since 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.	Hoy (2020); Wingen et al. (2022)
Rebuttal	A written response to a criticism made against a research manuscript or proposal. It aims to refute or dispute opposing arguments by presenting counter-evidence or alternative interpretations or theories. Thus, rebuttals are an important aspect of peer review processes, which 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	Henderson & Chambers (2022)

	journal, which is then peer-reviewed before any data is collected. If the proposal is deemed to be methodologically sound and potentially impactful, the journal agrees in advance to publish the results of the study, regardless of the outcome.	
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)
Scooped	A slang term used when one's research idea, study, or result is being claimed by other researchers, e.g., through publishing first.	Laine (2017)
Senior author	The senior author is the lead person (e.g., classically the principal investigator; PI), 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)

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? ● Is funding available to conduct the project? ● What are the time plan and work packages of the project? ● Who is responsible for what in the project?

2) Study design	● What are the hypotheses and how can they be tested? ● Which independent variables (IVs) are manipulated? ● Which dependent variables (DVs) need to be measured? ● Is approval by an ethics/institutional review board (IRB) 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? ● Do all manipulations work as intended?
5) Data collection	● How can we make sure my data is safely stored, accessible, and backed up? ● Is the data collected in a way that protects private information?
6) Data validation	● How can we ensure the quality and accuracy of the data? ● How can we store the data reproducibly?
7) Data analysis	● What are specific analysis pipelines and programs that can be used for specific types of data (e.g., EEG, (f)MRI, behavior)? ● What open-source software is a good alternative to proprietary products? ● 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 paper? ● 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? ● Is the published data FAIR (“Findable, Accessible, Interoperable, and Reusable”)? ● 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 your research to a lay audience?

Therefore, a comprehensive overview of curated resources that cover all parts of a research project is warranted. 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 (see also Figure 1 and exemplary resources marked with ➜ in the subsequent text). We named our tool ARIADNE, as we aim to help ECRs navigate the 'labyrinth' of research tools and resources, much like the mythological Ariadne helped Theseus navigate the labyrinth (e.g., see here). We named our tool ARIADNE, as we aim to help ECRs navigate the 'labyrinth' of research tools and resources, much like the mythological Ariadne helped Theseus navigate the labyrinth (e.g., see here). Our tool spans the whole research cycle, helps ECRs to identify and find relevant resources, and is available as a dynamic interface for easier use and searchability. The *open-access* database covers a constantly growing list of resources that are useful for each step of a research project, ranging from the planning and designing of study, over the collection and analysis of the data, to the writing and disseminating of findings. In doing so, we put an emphasis on open and reproducible science practices, as these practices become more and more valued and even mandatory (Kent et al., 2022). In the following, 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 , ultimately aiming to facilitate training and communication between experts and people starting out in the world of academia (see Table 1 and italicized words in the main text; for open science-related terms see Parsons et al., 2022). Lastly, we provide a checklist with questions one might ask at each step of a research project in Table 2.

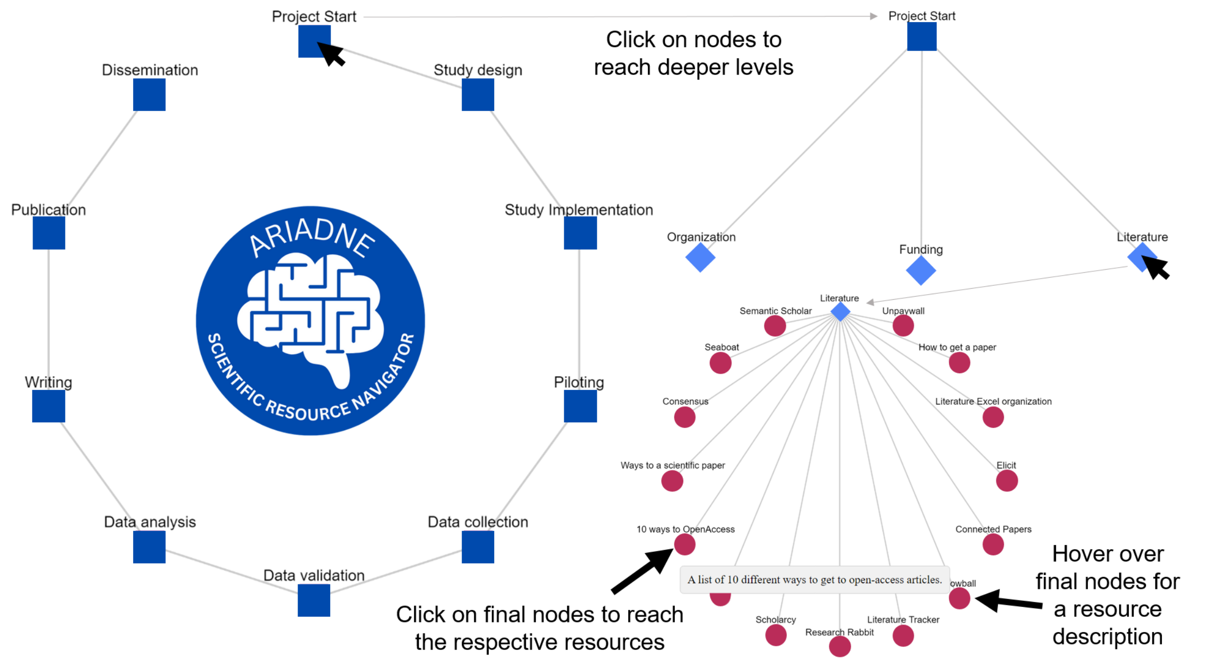

Figure 1. Exemplary visualization of ARIADNE - the scientific resource navigator. Clicking on nodes leads to deeper levels (black arrow keys), with the final level showing all associated resources including descriptions and hyperlinked websites (e.g., Project Start → Literature → 10 ways to Open Access).

Step 1: Project start

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. Critically, a research gap or limitation of previous work should be derived from the literature (Pautasso, 2013). This requires a comprehensive and systematic literature search, using subject-specific databases and search engines, which are listed in **ARIADNE** (e.g., ➜ PsycInfo, American Psychological Association (APA); ➜ PubMed, National Institutes of Health). However, novel research findings that are still in the peer-review process cannot be found via these databases. Therefore, researchers should also widen their search towards *preprint* repositories (e.g., ➜ bioRxiv or ➜ PsyArXiv) for appropriate content, keeping in mind that the latter work has not been peer-reviewed yet. Adopting an open science approach is also useful to avoid one's idea or project being *scooped* by other researchers (e.g., a *preregistration* or *Registered Report* documents one's original ideas; Laine, 2017; e.g., ➜ Connected Papers or ➜ Research Rabbit; see Table 1). Moreover, direct or conceptual replications of prior work have been highlighted to be critical to scientific progress (Nosek & Errington, 2017). 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; e.g., a behavioral study before employing more complex and costly neuroscientific methods). One should also consider whether the research question can be answered in the time available, in particular if they work on fixed contracts. Researchers who work on a joint research project have to discuss (and document) the responsibilities of each member of the project teams. Possibly, during the following steps, the research group may realize that further expertise is required, which can lead to the inclusion of additional co-authors. Finally, the research group should ideally establish a workflow pipeline that outlines the subsequent steps (i.e., Steps 2 to 9; Gantt charts: bar charts used to illustrate a project schedule, showing start and finish dates of activities 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)

Step 2: Study design

In an empirical research project, the study design encompasses conceptualizing and planning the methodology for data collection and analysis. Additionally, documenting the decision-making process throughout the research project is crucial for enhancing reproducibility, enabling other researchers to understand and replicate the study with greater ease. It is essential to maintain flexibility in this pipeline, allowing for adjustments as the project progresses. In this step and for most empirical research projects, approval by the local ethics committee should be applied for. Another important aspect of the study design step is determining the appropriate sample size, target population (e.g., neurotypical individuals or patients), as well as 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, e.g., via a *power analysis* (➜ G*Power, ➜ Justification Shinyapp, or ➜ g_ci_spm; Cohen, 1962; Jones et al., 2003; Kemal, 2020; see Table 1). Considering ethics in experimental design involves taking steps to protect the rights and welfare of participants, weighing costs and benefits while minimizing risks, and ensuring the privacy of participants and the confidentiality of their data. It also involves considering the impact of the findings on society and potential biases that may exist in the study. In essence, the study design step lays out the foundation for the entire project and provides a roadmap for all subsequent steps. Most importantly, it considers data collection, analysis, and interpretation of results (Steps 5-8). 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. Drawing on the experience from supervisor(s), mentor(s), and/or collaborator(s) is key in this step, as they might have specific expertise or experience with certain aspects of the planned project. In this step, the importance of 'Big Team Science' and sharing of knowledge and expertise becomes especially clear (Hall et al., 2018). **ARIADNE** can help kick-start this process by providing grounds for tool selection. In this step, criteria, tasks, and rules for (co-)authorship should be discussed already at an early stage of the project, and re-discussed over its course if changes arise (➜ *CRediT statement*; Brand et al., 2015; Tay, 2021; see Table 1 and Step 8). Finally, 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 freely available (➜ Psychopy vs. ➜ Psychtoolbox in Matlab).

Step 3: Study implementation

Study implementation refers to the development of a task or paradigm that will be used to manipulate the independent variables (IVs) and measure the dependent variables (DVs) of interest, as well as the creation of the necessary stimuli and control conditions. Here, stimulus control refers to the methods used to control and manipulate the stimuli that participants are exposed to during the experiment. This might include creating specific visual, auditory, tactile, or other types of stimuli, as well as controlling the timing, duration, and intensity of the stimuli. The selection of openly available stimuli on platforms such as the ➜ Kapodi Stimuli database or ➜ International Affective Picture System (IAPS) is recommended enhancing not only reproducibility, but also ensuring the use of stimuli that underwent a proper standardization procedure (Lang et al., 2008). **ARIADNE** helps in providing curated, tried-and-tested resources. Crucially, and of note, the trap of “questionable measurement practices” as indicated by Flake (2020) should be avoided by favoring materials proven for standardization, reliability, and validity (e.g., stimuli, tasks, questionnaires). However, researchers should consider that task reliability can mean different things in experimental and correlational research (Hedge et al., 2018; Nebe et al., 2023). Other aspects of study implementation may include the development of a *standard operating procedure* (SOP; Maghani, 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, as those will be relevant for the later writing process (Step 8). 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, has received a great deal of attention recently and been employed as a crucial tool in transparent and reproducible scientific research (Toth et al., 2021; see Table 1; ➜ PROSPERO for systematic reviews or ➜ Open Science Framework templates). This practice helps to prevent an inflation of the false-positive rate 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; see Table 1), even shift 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 investigation. This is often a reflective and iterative process (Thabane et al., 2010). By setting criteria based on important feasibility objectives and research goals, these pilot studies enable researchers 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). First, regarding feasibility, it is common and recommended to always test a few "pilot" participants with your whole set-up before starting Step 5 (the data collection), to test if participants understand the instructions of the new experiment and all procedures work as planned. The design of the main study can then be modified for improvements based on the findings of this pilot study. Of note, another complementary method for better determining a study's feasibility is to simulate data, which allows researchers to test multiple hypotheses and prepare for prospective outcomes before carrying out the primary investigation. Second, on an operationalization level, these preliminary data should be used to check whether all dependent variables can be extracted from the raw files. It is also important to note here that data from pilot studies or participants should be kept separate from the data of the main study. Crucially, it is considered controversial to use pilot data to calculate preliminary estimates of the effect size and variability of the outcome measures to estimate the required sample size for the main study (Albers et al., 2018; Sakaluk, 2016). In conclusion, piloting and data simulation are essential steps 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, it is recommended to 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. Note that writing up the method section before Step 5 promises to save time prospectively and enhances the precision and reproducibility of the research project. Here, data management strategies such as intuitive data saving structures can help to avoid misunderstandings as well as waste of time due to data rearrangement or rewriting scripts (Michener, 2015). Making sure you have all data backed up 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). 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 the ➜ Brain Imaging Data Structure (BIDS; Gorgolewski et al., 2017) for complex neuroimaging data, which are listed in **ARIADNE**. Furthermore, data anonymization or pseudonymization are critical techniques to protect participants' rights and privacy (Meyer, 2018 for ethical data sharing; Hallinan et al., 2023 for European Union regulations on data privacy). **ARIADNE** also provides examples of existing data that can be used for some research questions.

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., Breck et al., 2019 for machine learning projects and our tool **ARIADNE** for specific resources). 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 or outliers (Freire, 2021). This may include checks for missing data, incorrect data entry, or other issues that could impact the validity of the study and subsequent interpretation of the results, but also assuring your data is FAIR ("Findable, Accessible, Interoperable, and Reusable" ➜ FAIR data or ➜ RDMkit), which will facilitate the later publication of the data along with the paper (Step 9). *Data wrangling*, also known as *data munging*, is 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 (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 cleaning process, and storing the raw and processed data in a secure and accessible format (which might mean that the software [version] used to gather and process data has to be stored as well). However, aspects like data quality, merging data from different sources, creating reproducible processes, and data provenance are equally important. Importantly, these validation practices should be implemented throughout the data collection. In sum, this step contributes essentially to the robustness of the study's findings and the ability to replicate or build upon the research in future studies. This step can be started as soon as first data is collected, leading to the next step, data analysis.

Step 7: Data analysis

Classically, 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 (Hueber et al., 2016). This process includes metadata setup, data cleaning/screening/refining, updating the research analysis plan, 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 as part of a preregistration or Registered Report. But even then, many new decisions have to be made at this stage, which may affect the next steps, e.g., how the data can be best shared with others 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). Statistical approaches that are suitable for the research question need to be chosen (e.g., Bayesian versus 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). In the processing of analyzing results, it is essential to consider the role of visualizations. Effective visual representations can enhance the comprehension of complex data sets and findings (➜ BioRender; ➜ Mermaid; ➜ Nipype). 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 1 error* rate (Lakens, 2014). 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). Of note, data analysis is a critical step that has attracted much attention recently in light of the so-called “replicability crisis” (Anvari & Lakens, 2018), as this is a stage where questionable research practices (John et al., 2012) and biases may occur (even inadvertently).

Step 8: Writing the manuscript

Once data is analyzed and discussed with supervisor(s) and potential co-authors, researchers are set to outline their results in a comprehensive manuscript (Mensh & Kording, 2017). In this context, they need to determine a target journal for their manuscript. This journal should ideally be related to the research question, and will subsequently influence the scope of the paper (e.g., audience, article structure). Various criteria can guide the journal selection (Salinas et al., 2014). Criteria like *impact factor* (see Table 1) and journal prestige may be critical for more senior researchers who need to build-up a reputation, whereas criteria like acceptance rates and turn-around times may be more important for ECRs who need to complete their academic training within a limited amount of time.

The decision for a target journal is usually taken together with the project team (i.e., supervisor, collaborators, and co-authors, see also Step 1; ➜ Journal-Author Name Estimator), and will often specify the 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. Moreover, journal choice will directly affect how the article can be accessed (e.g., *open-access* or *paywall*) and whether and how pre- and *postprints* can be shared with the scientific community (see Table 1). Authorship of the manuscript should be offered to individuals who agree to make substantial scientific contributions to the project (see APA Ethics Code Standard 8.12a, for example; see also Step 1). These include, but are not limited to, conceptualization, data collection, data analysis, writing, funding, or supervision.

However, the status and order of authors varies strongly depending on the scientific discipline (Pain, 2021). In human neuroscience and psychology, the order of authorship usually reflects the relative contributions of the researchers involved (e.g., ➜ Credit Author Statement; ➜ Tenzing). While 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. Other fields may opt to include people with minor contributions or choose an alphabetical author order (Pain, 2021).

Step 9: Publication

There are many ways in which to disseminate scientific work (Bourne, 2005; see Step 10) or are summarized in **ARIADNE**. Preprints facilitate early access to the manuscript, which helps researchers to document their scientific or academic work and may even be used to assert priority (e.g., ➜ MetaArXiv or ➜ BioArXiv). Preprint publication often happens simultaneously with the submission to the target journal of choice. The accessibility and reception of a preprint may make it easier to assess the quality of scientific work than bold claims about the novelty or impact of the work (Brembs, 2019). However, be aware that some journals prohibit the upload of preprints (➜ Sherpa Romeo). Additionally, fellow researchers who have access to this work may provide comments that may be useful for a critical re-evaluation of the manuscript, which might also happen simultaneously to its *peer review* at a journal (see Table 1). 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 also actively discourage the submission of a cover letter to let the manuscript "speak for itself". Once the manuscript is under review, reviewers might raise more or less critical issues about the manuscript and inform the editor handling your paper (Suls et al., 2009). More often, the editor then recommends either acceptance, minor revisions (both rarely happen on the first submission), major revisions (sometimes also called *revise and resubmit*; see Table 1), or rejection. 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 to argue why suggested changes have not been adapted. 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). This process until seeing your paper published can take several months (in rare cases even years) and this time should be factored in Step 1, where a time plan of the project is first fixed. If your manuscript is rejected by your first journal choice, a submission to an alternative journal of equal or slightly lower rank is usually warranted. Only in exceptional cases an appeal could be considered. 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 co-authors and corrected in the published article as soon as possible (Bruns et al., 2019).

Step 10: Dissemination

Once a study has been pre-printed and/or published, the dissemination process does not necessarily end, and **ARIADNE** showcases the many ways in which you can continue to publicize or present your work (Bourne, 2007). It can be important to pursue additional dissemination strategies in order to reach as many people as possible to benefit from the new findings (Ross-Hellauer et al., 2020). Typically, the results should be presented at conferences in the form of talks or posters (Pain, 2022), and potentially circulated on online platforms (e.g., ➔ X 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. Generally, two target groups should be differentiated when it comes to dissemination: Other researchers and the general public. Regarding the latter, 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. Ultimately, sharing open materials, including codes and data (Contaxis et al., 2022) with licenses, is highly favorable considering the rise in open science practices. The 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 an appropriate platform (➜ Open Science Framework or ➜ Zenodo). A wide-reach dissemination strategy is highly recommended. Eventually, research only has value when the methods and results leave the academic *ivory tower* (see Table 1) and are communicated to the general public and stakeholders.

Discussion and outlook

With this comprehensive overview of the ten most important steps of a research project and their inherent respective challenges, we present our tool **ARIADNE**. By introducing ARIADNE to the research community, we provide 1) a step-by-step guide on how to perform a research project, 2) an overview on resources that are useful at the different steps of such a project (with a specific focus on open and reproducible science), and 3) a glossary of most common terms surrounding the research cycle. By focusing on open-access and open-source resources, we level the playing field for researchers from underprivileged countries or institutions. We also facilitate open, fair, and reproducible research in the field of neuroscience, and empower ECRs to master reproducibility and replicability challenges with this living and dynamic open resource platform.

We think that providing an accessible and structured overview of resources with a focus on open science will be of utmost importance to ECRs, particularly since institutions, funding agencies, and other stakeholders are laying more and more weight on efforts in improving scientific quality (see, for instance, the ➜ Declaration on Research Assessment, DORA). Facilitating the integration of open science practices and improving research quality through collections such as **ARIADNE** will thus be an important contribution to advance the careers of ECRs. We nevertheless hope that our paper and tool can be widely distributed to researchers of all levels starting a new project, but also to supervisors as a guideline or tutorial for their employees. As our resource is “living” and “interactive”, we also actively call experienced researchers from our, but also other, neighboring fields to contribute their own tried-and-tested tools to our database here.

As a team of ten researchers at different career levels, including PhD students, postdocs, and professors, we bring extensive experience and knowledge in using these resources, many of which are regularly employed in our own work. The resources provided in this manuscript 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. We cannot guarantee the effectiveness, suitability, or long-term availability of any particular resource for a specific research project, but we will regularly update and add resources with a dynamic, quality-driven approach. Researchers are encouraged to exercise their own judgment and discretion when selecting resources and conducting experiments.

We would further like to stress that the present version of the tool is a starting point, which we aim to continuously extend and improve upon. 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 (Nature Human Behaviour, 2021), as well as time management, progress tracking, and grant writing (Bourne & Chalupa, 2006).

In conclusion, we believe that this resource holds promise to encourage not only early career scholars, but also more senior researchers, delving into the field of open and reproducible science, using our tool as a starting and orientation point. Together, we can greatly alleviate the challenges attached to starting out in science, prevent a constant, frustrating “re-invention of the wheel”, and provide helpful support during all stages of the research cycle – for everyone.

Author contributions

- Conceptualization: All authors
- Data curation: All authors
- Investigation: All authors
- Methodology: All authors
- Project administration: HH, CG
- Software: CG, MM, AKa
- Supervision: HH, CG
- Validation: All authors
- Visualization: HH, CG, MM, AKa
- Writing – original draft: HH, MFJS, AL, YY, AKo, SV
- Writing – review & editing: All authors

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Competing interests

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Data accessibility statement

Our step-by-step tool **ARIADNE** is freely available online and hosted on GitHub, using Cytoscapes.js and JupyterBooks. It complies with the Open Source definition. Find the matching website here and the tool itself here. New resources and/or feedback can be submitted via this form.

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