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A quantitative account of how limited information sharing undermines comprehensive literature syntheses

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ABSTRACT

Crucial aspects of reproducible, replicable and reusable science include the responsiveness of study authors for clarifications and the availability of research data and analysis results. Getting in contact with authors and obtaining information or results is, however, not always straight-forward. Here we report and discuss the issues and obstacles we faced when contacting authors of scientific papers with such requests. Our investigation rests on the results of a retrospective quantitative analysis of research data requests sent to authors of neuroimaging studies for a series of meta-analyses. Overall, only 52% of the requests received a reply, and only 29% contributed data or information that was relevant for the respective meta-analysis. Obtaining a response was less likely if (i) the request was sent to the contact e-mail address provided in the publication, (ii) behavioral data was requested, (iii) reminders had to be sent, or (iv) there was no personal acquaintance with the contacted author. As expected, obtaining unpublished data or information from older publications was significantly more difficult than for more recent ones. We discuss possible reasons for the observed low response rates and limited sharing of information and conclude our account by providing suggestions to improve open-science practices and by pointing to a need for change in the academic system to foster better research data management for transparency and efficient reuse of results.

1. Introduction

Science should be conducted according to the principles of good scientific practice, aiming to provide solid results that are not incidental. This implies reproducible and replicable science, i.e. reporting results that are consistent when repeating the experiment using the same input data and analysis code as the original publication (reproducible) or using own data (replication) (National Academies of Sciences, E., Medicine., 2019). A cornerstone in this endeavor is open science, i.e. transparent reporting and data sharing (Nosek et al., 2012; Rouder, 2016). To this end, many initiatives (for example Gorgolewski et al., 2015; Markiewicz et al., 2021; Nosek et al., 2015; Vaccarino et al., 2018) and reporting standards (for example EQUATOR (Altman et al., 2008), COBIDAS (Nichols et al., 2017), PRISMA (Moher et al., 2009)) have been proposed. Yet, a substantial amount of data is unavailable, and publications often lack detailed information on methods and results (Hardwicke et al., 2022; Sherry et al., 2020; Tedersoo et al., 2021).

Beyond the need for raw data for replication and reproducibility,

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researchers often also need the results of published articles for follow-up analyses (for example for region of interest analyses in neuroimaging studies) or for inclusion in systematic reviews and meta-analyses. Especially for the latter, adequate reporting in original research papers is essential, as both research synthesis methods can only consider studies that provide specific pieces of information. Unfortunately, however, data or information required for meta-analyses or follow-up analyses is often missing or unclear, which is not always due to sparse or intransparent reporting but may also result from a mismatch between the research question of the original study and the focus of the meta- or follow-up analysis. For example, experimental clinical studies using a case-control design often only report between-group differences, while within-group effects from the healthy control group would be of interest for, say, a meta-analysis focusing on this effect in healthy populations. Thus, sharing of unpublished group-level results is crucial for use in subsequent research projects by other research groups. Especially in neuroimaging, it is increasingly necessary to have results available for secondary or follow-up analyses given the high cost of data acquisition. Importantly, data-sharing platforms can not necessarily solve this issue as not all potential follow-up analyses as well as topics of future meta-analyses can be foreseen at the time of publication.

To reduce the number of excluded studies, meta-analysts often contact the authors of an original study and request missing information or unpublished results (for example Ficco et al., 2023; Langner and Eickhoff, 2013; Müller et al., 2024). In fact, for systematic reviews and meta-analyses, it is recommended and common practice to contact authors to collect unpublished data, data reported in the grey literature (e.g., theses, in-house reports, conference abstracts), or data from already published work that did not provide certain relevant information or lack sufficient details for inclusion (Forero et al., 2019; Lefebvre et al., 2023; Meursinge Reynders et al., 2019). Importantly, key results of meta-analyses can change when including information received from authors upon request (Meursinge Reynders et al., 2019), and direct analyses of the influence of unpublished data (e.g., sensitivity analyses) are only possible if such data are provided.

In summary, for researchers, and meta-analysts in particular, it is often critical to obtain additional information or results from group-level analyses directly from authors of publications. Getting the requested information is, however, often more challenging than would be desirable for scientific research. Previous studies that investigated the response and data sharing rate of authors have often contacted only authors of articles that explicitly state that data will be shared on request (Krawczyk and Reuben, 2012) or of top-cited articles (Hardwicke and Ioannidis, 2018) or high-impact journals (Tedersoo et al., 2021). Additionally, all previous work requested raw data for replication purposes, which might involve more obstacles for sharing than does asking for aggregated data for follow-up analyses. That is, sharing of raw data might to a stronger degree involve issues previously identified as main barriers for data-sharing (Houtkoop et al., 2018; Paret et al., 2022) including legal constraints on sharing individual human data or dreaded disadvantages (i.e., getting scooped, fearing that someone finds a mistake in the data or cannot reproduce the findings). Thus, the accessibility of aggregated group-level data (in contrast to raw data) or study-related information might be better for purposes other than replication efforts based on raw data. Here, we present and discuss the issues and difficulties we encountered when contacting authors of scientific papers with requests for information via e-mail in the context of seven neuroimaging meta-analysis projects conducted by our research team. In these requests, we non-randomly contacted authors and asked for information not reported in the publication (mostly results of group-level neuroimaging or behavioral analyses) or for clarifications about reported results and methods. Our observations and discussion will focus on author responsiveness as well as the preparedness and ability of authors to help. This provides an overview of issues to be considered by meta-analysists and other (neuroimaging) researchers when contacting study authors to request information or data.

2. Methods

2.1. Data requests

We retrospectively analyzed e-mail requests in the context of seven projects (one of them unpublished) conducted in our research team (Ficco et al., 2023; Gell et al., 2024; Heckner et al., 2021; Kraljevic et al., 2024; Küppers et al., 2024; Müller et al., 2024), in which authors of neuroimaging studies were contacted. These projects were all meta-analyses, which therefore required systematic and comprehensive inclusion of data and detailed information for checking if inclusion criteria are met. Authors were contacted when required information or data was not reported in the selected publications, nor available in supplementary materials or online repositories. Contacts were made via e-mail using an institutional email address of the contacting authors (VK, NK, VM, ST, LF, MN, MG, RK). In these e-mails, we briefly introduced the aims of the project for which data were needed, we explained the kind of data we were looking and we stressed the importance of including unpublished data in meta-analyses (see supplemental material for an example of such an email request). In case we requested results of neuroimaging functional contrasts as data, we made explicit reference to the type of effect we were interested in, the experimental conditions of interest, and the neuroimaging contrast that best captured the effect under study.

Our contact strategy involved several steps: first, the corresponding author was contacted, using the address reported in the publication; if a failed delivery message was obtained, we looked for an up-to-date e-mail address of the respective author. If no contact information was retrievable for the corresponding author, we tried to contact other authors, primarily the senior author. Non-corresponding authors were contacted if (i) we received an e-mail delivery failure message from the corresponding author's address and no information about this author was available online, (ii) one of the other authors was personally known to a team member, or (iii) we were re-directed to a particular author from the corresponding author whom we had contacted first. Up to two additional reminders (see supplemental material for an example) were sent some time (about 1–3 months) after the first unanswered contact attempt or, in some cases, after the first response from some authors who had written they would send information (but did not). Given the retrospective nature of data collection, the sending (if and when) of reminders was non-systematic and depended on the specific project and its timeline (for some projects there was no time left to send reminders). Importantly, authors could also get more than one request, either because we requested data from different publications of a given author or asked for different data related to a given publication in the context of different projects. Similarly, more than one request could be sent to different authors of the same publication due to failed deliveries or redirection to other authors from the corresponding author.

2.2. Information extracted from the requests

For each data request, we extracted both the overall responsiveness (whether we received at least one answer to our request or a reminder) and the outcome (whether we were able to obtain the requested information in the end). For responsiveness, any non-automatic response from the author was counted as "response", while no responses as well as automatic responses for which no updated email address was found were counted as "no response". For categorizing the outcome, we first noted down whether we received relevant information ("information sent" vs. "no information"). We counted responses as "providing relevant information" if we actually received data or information that we could use for our analyses, but also if the response led to the exclusion of the study (e.g., the information that the respective contrast was not calculated and was thus not available). For requests for which we received a response, but no relevant information was sent, we categorized the response into four categories (no access or cannot find it/will send/redirection to another author/other). In some (rare) cases, authors were willing to share data, but only in exchange for co-authorship or any other incentive. These responses were categorized as "no information" and into the category of "other" as reason for not sharing. Beyond overall responsiveness and outcome (what was the response and outcome at the endpoint), we also extracted the respective information (response, outcome, detailed outcome and reason for not sharing the data) also for each email individually (first request and reminders).

Additionally, we coded the following information: what kind of data was requested (behavioral, neuroimaging, clarification about the study), whether the contacted person was the corresponding author, whether the e-mail address used was that reported on the paper, the position of the corresponding author in the paper (first/last author/other), the time span between our request and the year of publication of the paper, whether our first contact occurred before (January 2020), after (April 2022) or during (between January 2020 and April 2022) the COVID-19 pandemic, if there was personal acquaintance with the contacted author as well as the number of reminders that were sent.

2.3. Data illustration and statistical analyses

We calculated overall response and outcome frequencies as well as frequencies of different categories of reasons for not sharing information. Besides calculating descriptive statistics, two analyses using a generalized linear mixed model (GLMM) were performed to investigate the role of potentially relevant factors on the likelihood of overall response and of receiving the requested information, accounting for multiple requests per author. In a first step, we coded factors of interest as two-category dummy variables, i.e. e-mail address used (same/different e-mail as on the publication), authorship position (first author/other than first author), contact during COVID-19 pandemic (yes/no), reminders sent (yes/no), personal acquaintance with the author (yes/no). Both GLMMs were fitted using a binominal distribution with a logit link as the dependent variables were binary. In both models, we included the five dummy-coded categorical fixed factors (i.e. e-mail address used, authorship position, contact during COVID-19 pandemic, reminders sent, personal acquaintance with the author) and the continuous predictor time span between date of request and year of publication. AuthorID was modeled as random intercept and the covariance structure of the random effects was specified as unstructured. Fixed-effect degrees of freedom were approximated using the Satterthwaite method. For both GLMMs, the assumptions of (i) linearity between the continuous predictor (time span) and the link-transformed dependent variables (receiving a response, receiving the requested information) and (ii) lack of multicollinearity were met. Unfortunately, the random effects did not follow a normal distribution, which is why we performed additionally sensitivity analyses, fitting binary logistic regression and ignoring dependencies between requests to the same authors. These analyses yielded the same significant effects. Therefore, and because the random effect in the GLMMs explains a meaningful portion of variance, we report the GLMM results to account for dependencies in the data.

In addition to overall response and outcome, we assessed response rates and outcome and reasons for not sharing also at the level of first contact and reminders.

Analyses were conducted using SPSS (version 31.0.1.0). Descriptives were illustrated by bar charts using SPSS as well as Sankey Diagrams using SankeyMatic (https://sankeymatic.com/).

Data and scripts reported in this article are available on OSF (https://osf.io/43nra/?view_only=680711dc4f1b45439e615d8defb19076).

3. Results and discussion

3.1. Responsiveness of authors

Our investigation covers the time from April 2017 to March 2023, in which we sent 377 requests overall, contacting 291 different authors and asking for group-level results or non-reported information from 297 different papers (for more details see supplemental material). We requested information from publications that were between 0 and 21 years old (median of 5 years, Figure S1A), with a distribution skewed to more recent publications. Of these requests, 52% (195) received a response, while 48% (182 requests) did not receive an answer at all (Fig. 1). This response rate is comparable to the rate reported for requests of raw data in biomedical science in general (Teunis et al., 2015) and slightly lower than reported for most other disciplines (Hardwicke and Ioannidis, 2018; Krawczyk and Reuben, 2012; Tedersoo et al., 2021; Vanpaemel et al., 2015; Wicherts et al., 2006). Only for the fields of biology and forestry, response rates have been reported to be worse (< 40%, Tedersoo et al., 2021; Vines et al., 2014).

Before discussing issues and reasons for a lack of response, it is important to note that even though response rates for group-level data and clarifications are far from perfect, for meta-analysis it is still worthwhile to contact authors for further information on publications. That is, because of our requests and the responses obtained, we were able to include 90 additional studies in our meta-analytical projects overall, increasing their statistical power and comprehensiveness.

Various factors influence the chances for obtaining a positive response. In particular, response rate was significantly influenced by whether the request was sent to the email address provided in the paper ($\beta = -0.86$, $p = .005$), by the complexity of the data requested ($\beta = 1.09$, $p = 0.003$), if there was personal acquaintance with the contacted author ($\beta = -2.08$, $p = 0.007$) and if reminders were sent ($\beta = 0.84$, $p = .002$). No significant modulation of response rate was observed for authorship position ($\beta = 0.16$, $p = .54$), for whether the request was sent during the COVID pandemic ($\beta = 0.26$, $p = .33$), or for the time span between request and publication of the paper ($\beta = -0.04$, $p = .23$). These outcomes should be considered when there is the need for contacting authors for unpublished information and will be discussed in the following.

3.1.1. Potential reasons for a lack of response

3.1.1.1. Outdated contact information. In case some clarification or additional information with respect to a publication is required, the first question always is: whom to approach? In case one of the authors is personally known, this author will naturally be selected for correspondence, and our data suggests that this approach is quite effective for receiving a response (odds ratio [OR] =7.96, Fig. 2D). However, quite often there is no personal acquaintance with the authors of publications. Responding to publication-related requests and queries is, in principle, one of the responsibilities of the authors of a publication, especially of the corresponding author. Indicating a corresponding author at submission of a paper is actually required by most journals, mainly to handle the correspondence with the journal during submission, review, and revision (van Loon and van Loon, 2023). However, the corresponding author's contact information is also provided in the paper after publication, indicating the person to be contacted for post-publication queries (Birnbaum et al., 2023; van Loon and van Loon, 2023; Zauner et al., 2018). This post-publication responsibility is often not explicitly mandated by publishers (Birnbaum et al., 2023), that is, it is an unwritten rule without any enforcement by the publisher. Indeed, given that almost half of our requests were not answered at all, this responsibility, quite obviously, has often little priority. This does not necessarily suggest that all non-responsive authors were uncooperative or ignored their communication responsibility. Rather, authors often

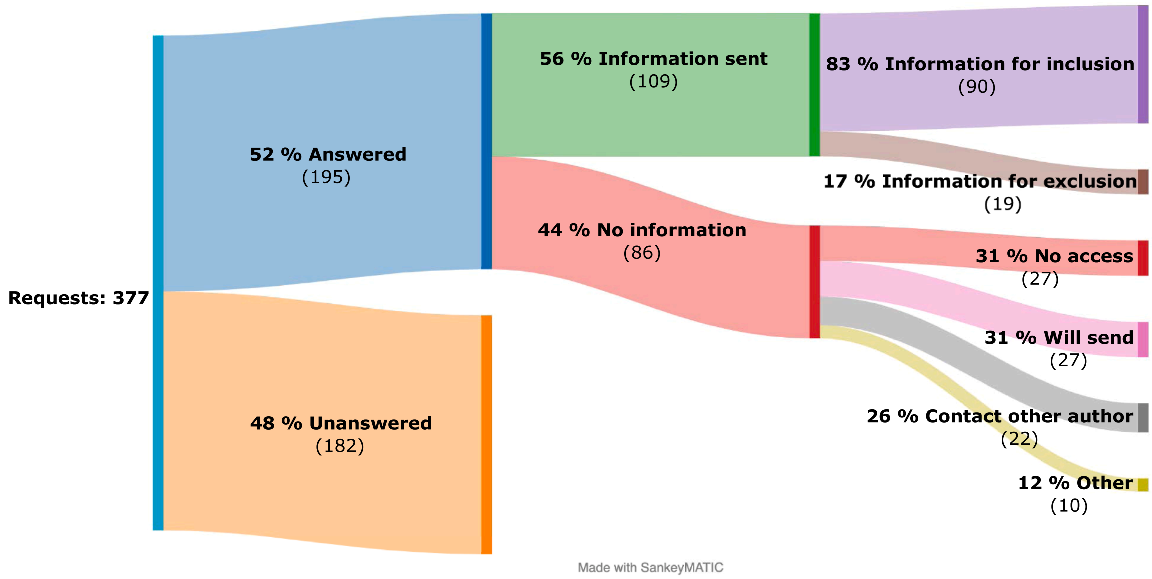

Fig. 1. Outcomes of 377 e-mail requests for information, illustrating response and data sharing rates as well as the types of answers received if data was not shared.

might not consider this responsibility when designating the corresponding author and providing their email address in the paper. Researchers are only human: they may change work positions, will retire at some point, and eventually pass away. Yet, this is often neglected, and the corresponding author is selected for reasons of scientific credit (van Loon and van Loon, 2023) or preferences of the senior scientist (Birnbaum et al., 2023), mainly considering the short-term goal of providing contact information for correspondence with the journal and disregarding the long-term responsibility of dealing with post-publication queries. Senior authors often prefer not to be involved in the work associated with the submission process of an article, while junior researchers aim for scientific credit of their work. As a result, junior first authors often are designated as corresponding authors (Chinchilla-Rodríguez et al., 2024; Yu and Yin, 2021), providing their personal academic email addresses for correspondence. These email addresses, however, often are short-lived, given that junior scientists often transfer to other research institutions (Deville et al., 2014; Guthrie et al., 2017; Van Noorden, 2012) or move to jobs outside academia (Hancock, 2023; Hayter and Parker, 2019; Kaminski and Geisler, 2012). One of the reasons for not receiving responses might thus be the high staff turnover rates in academia, especially among young scientists with non-permanent positions. Accordingly, many corresponding author e-mail addresses are dead ends because they are not monitored anymore, at least not regularly, or have simply ceased to exist. This assumption is further supported by our data. When performing GLMMs to investigate the role of potentially relevant factors we found that the response rate was significantly influenced by whether or not the request was addressed to the e-mail address provided for correspondence in the paper (β = - 0.86, p = .005), with a lower likelihood for an answered request if the provided email address was used (odds ratio [OR] = 0.42), as compared to using a different – and potentially more recent – e-mail address (Fig. 2A). Although, the e-mail address used for correspondence does not completely reflect staff turnover and affiliation changes, we still interpret our results as indirect evidence and would even assume that the effect would be higher if we had information on the affiliation valid at the time of contact. Due to the retrospective nature of data analysis, we unfortunately could not extract this information from the data requests used here.

The problem of inaccessible corresponding authors has been previously discussed for other research fields (Teunis et al., 2015; van Loon and van Loon, 2023). Not surprisingly, it also is a problem in the domain of neuroimaging research. A potential solution to this issue is providing the ORCID (Haak et al., 2012) for the corresponding author, a unique personal identifier for scientists. As it "is persistent, it is immune to employment changes" (p.1, Cress, 2019). Additionally, assigning more than one corresponding author or creating and using a lab e-mail address for correspondence could also help. Of course, a lab e-mail address needs to be managed in addition to personal addresses, the ORCID profile needs to be kept up to date, and it will not help in case a researcher leaves academia, retires, or passes away, but it can greatly reduce the number of authors who are out of reach for simple turnover reasons, helping to save time spent on investigating current contact information.

3.1.1.2. Type of information requested. Neuroimaging studies are usually rather complex in nature and require careful and detailed reporting of the data, analysis and results to make them understandable and assessable for other researchers (Nichols et al., 2017; Poldrack et al., 2008). To be qualified for inclusion in a neuroimaging meta-analysis usually requires not only the results of the imaging analysis per se but also specific information on the contrasts calculated and control conditions used as well as on sample characteristics and results from behavioral measures. However, systematic reviews of neuroimaging studies have shown that sometimes publications miss out on reporting detailed information about the design and contrasts (Acar et al., 2023) but also about basic demographic data such as sex and ethnicity of participants (Sterling et al., 2022).

When analyzing potential factors influencing the rate of positive responses to our data requests, we observed that the type of information requested showed a significant effect on the response rate (β = 1.09, p = .003), with a higher likelihood for a positive response if neuroimaging results were requested (OR = 2.96, Fig. 2B) compared to requests asking for behavioral information or clarifications. Given that most of our requests asking for less complex data were for behavioral data (only 6 of 80 requests asked for clarifications) from neuroimaging studies, our result suggests that the behavioral data from such studies is stored less systematically and less findable than the corresponding neuroimaging data. This, in turn, might be because the behavioral findings play only a secondary role and are considered less relevant for answering the research questions. Indeed, only a fraction of neuroimaging studies report analysis results for behavioral measures (Müller et al., 2024) but often solely focus on brain activation during the tasks. Furthermore, while in the original version of the reporting guidelines for neuroimaging data by Nichols et al., the importance of reporting

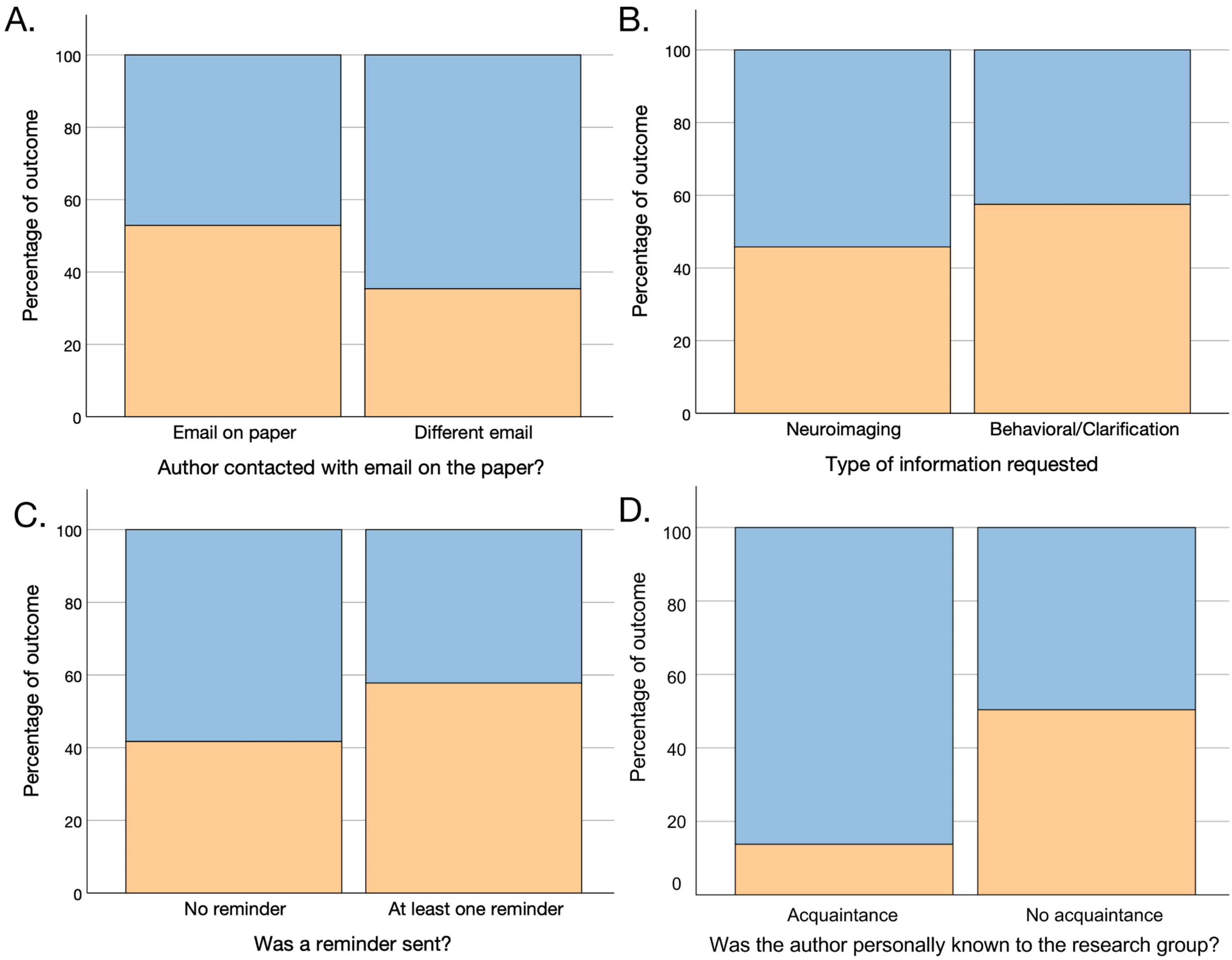

Fig. 2. Response rate (blue: answered, orange: unanswered) of contacted authors as a function of (A) the source of the email address used for the request, (B) the type of information requested, (C) whether a reminder was sent, and (D) whether there was personal acquaintance with the contacted authors. The likelihood of receiving a response was higher if a different e-mail address was used than the one provided in the paper, if neuroimaging results (vs. other types of information) were requested, if no reminder was sent and if the contacted author was personally known to the contacting research group. For better comparison between the two conditions of each factor, the y-axis represents relative frequencies of outcomes per condition.

behavioral data has been highlighted (see preprint version posted at bioRxiv in May 2016; Nichols et al., 2016), this recommendation did not make it into the final publication of the guidelines in Nature Neuroscience (Nichols et al., 2017). We speculate that this might reflect a tendency of the field to consider behavioral measures as a less objective, noisier measure of the constructs of interest (Rossion et al., 2020). Over the last decade, however, neuroscientific research has increasingly shifted its focus on brain–behavior correlations (Genon et al., 2018). Consequently, we might expect authors of neuroimaging publications to give more importance to behavioral data and store them easily findable and accessible for sharing in the future.

3.1.1.3. Age of the publication. Even though neuroimaging is a quite young scientific discipline, brain imaging has a history of more than 100 years where the relationship between blood flow and brain function has first been investigated. However, it took some more time for research to apply PET or fMRI for investigating human brain function, which roughly started more than 40 years ago (Posner and Raichle, 1994; Raichle, 2009). Thus, neuroimaging meta-analyses may include studies of greatly varying age. Given the turnover in academia, but also simply the aging and therefore retirement of scientists, it could be assumed that requests to authors of more recent publications are more promising. This is in line with previous studies (Tedersoo et al., 2021; Teunis et al., 2015) that reported a relationship between the recency of a publication and the response rates of authors. Surprisingly, we did not observe a significant modulation of the response rate by the time span between the request and publication of the paper ($\beta = -0.04$, $p = .23$; see Figure S1A for the distribution of the time spans between request and publication). This is most likely due to the fact that we investigated the influence of multiple factors and thus controlled for explained variance by the other predictors (e-mail address used, authorship position, time span between date of request and year of publication, contact during COVID-19 outbreak, reminders sent, personal acquaintance). Thus, the recency of a publication might still be of importance but only when using the e-mail addresses given in the paper. We searched for alternative e-mail addresses when a request could not be delivered and only counted those requests as failed deliveries if we were unable to find a presumably working alternative e-mail address. Vines et al. (2014) showed that the age of a publication was related to the probability of finding a working e-mail address but not to the response rate when only considering e-mails without a failed delivery message. We thus suggest that it might still be worthwhile to contact authors of older publications, but with the necessity to search for current contact details.

3.1.2. Does it help to send follow-up emails?

Academia is a highly competitive work environment, accompanied by a strong publication and time pressure, which may result in high levels of perceived occupational stress (Lee et al., 2022; Sabagh et al., 2018). As a result, responding to requests from other scientists for data or clarifications regarding already published work is often not the top-priority for researchers, especially if a substantive response would require looking into the publication and/or searching for the respective data or results, potentially analyzed by former colleagues. Thus, responses to requests might often be postponed and eventually forgotten, especially if there are no incentives for investing time to respond. In academia it is therefore common practice that follow-up e-mails and reminders are sent, potentially based on studies on response rates of surveys showing that reminders significantly increase response rates (Sheehan, 2001). However, beyond the few follow-up e-mails for surveys, researchers are often flooded by reminders for all kinds of issues. For instance, journals send reminders for article submission and review invitations, organizations follow up on conference invitations and grant calls, and there usually are numerous other reminders related to teaching and student supervision, talks and webinars, industry news, and so on. Given that reminders have become part of the daily routine for research, it is questionable if they help to increase the likelihood of a response. When requesting data from neuroimaging studies, we also sent reminders in the hope to increase response rates (supplemental results for details). 154 requests (118 of which had received no response and 36 requests where the author had responded that they will send information) were followed up by a first reminder, of which 33% (50 cases) were answered (with 28 cases not being answered when sending the first email; Fig. 3). For 24 of our initial requests, we sent a second reminder, with 25% (6 cases) of them being answered and 75% (18 cases) not (Fig. 3). Importantly, 5 of them already responded to the initial request, while only 1 of them only responded to the second reminder (i.e., to the third e-mail). Thus, descriptively we could increase the response rate from 44% of responses based on the initial e-mail to 52% after the second reminder (response to at least to one of the e-mails). Our generalized linear mixed model analysis also revealed that reminders had a significant influence on response rates ($\beta = 0.84$, $p = .002$), but with the likelihood for a response being higher when no reminder had to be sent (OR = 2.32, Fig. 2C). This clearly points to a selection effect, indicating that if authors do not respond to the first e-mail, a response to follow-up e-mails is also unlikely. In turn, people that tend to respond, do not necessarily need a reminder but already respond to the initial request (see Fig. 3 illustrating the distribution of reminder emails and their consequences).

3.2. Accessibility of unpublished neuroimaging information

3.2.1. Are authors sharing relevant information when being contacted?

Reproducible and replicable science requires transparent reporting and data sharing. However, despite a lot of initiatives, large amounts of data are still not available, and publications often lack sufficiently detailed information on methods and results (Hardwicke et al., 2022; Sherry et al., 2020; Tedersoo et al., 2021). Lack of data availability may be due to various obstacles such as legal or ethical constraints on sharing data, concerns about possible disadvantages for data contributors (i.e., fear of being scooped, being exploited without compensation, or errors being identified), time constraints, as well as the storage-space-intensive and complex nature of the data themselves (Houtkoop et al., 2018; Paret et al., 2022; Poldrack et al., 2013). Insufficiently detailed reporting, in turn, could partially result from publication pressure in academia and word limits of journals, especially those with high impact factors. Studies have shown that, depending on the discipline, between 26% and 59% of requests to authors for (mainly raw) data are successful (Hardwicke and Ioannidis, 2018; Krawczyk and Reuben, 2012; Tedersoo et al., 2021; Teunis et al., 2015; Vanpaemel et al., 2015; Vines et al., 2014; Wicherts et al., 2006). Additionally, it has been shown that the success of a data sharing requests strongly depends on the age of the publication as well as the complexity of the data (Tedersoo et al., 2021; Vines et al., 2014). Importantly, these data sharing rates mainly relate to the sharing of raw data, where legal issues may come into play related to the sensitivity of certain (e.g., biomedical) data as well as dreaded disadvantages in case of non-reproducibility. However, raw data is not the kind of data most meta-analysts are interested in. That is, in the context of our own research, we almost always requested results of group analyses for inclusion in coordinate-based neuroimaging meta-analyses. Importantly, we counted all responses as successful (i.e. as “sent relevant information”) that contained information or data that either led to inclusion in the respective meta-analysis or provided reasons for

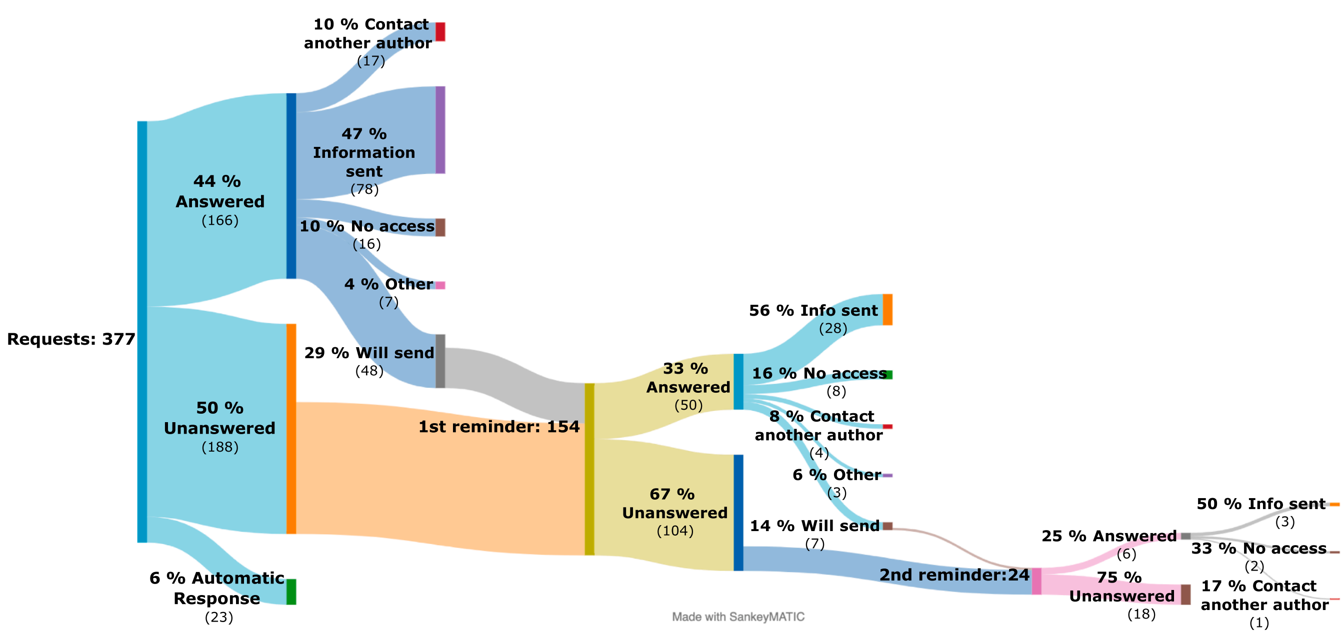

Fig. 3. Illustration of the distribution of reminders and their consequences.

exclusion (e.g., the information that the respective contrast was not calculated and is thus not available).

We observed that out of the 195 answers to our requests, 56% (n = 109) contained relevant information, with 83% (n = 90) of them providing information subsequently included in the respective project, and 17% (n = 19) providing information that led to exclusion from the meta-analysis (Fig. 1). Relative to our 377 requests that we sent out in total, 29% thus resulted in information relevant for the respective project. As such, the information sharing rate of group-level data for meta-analysis (29%) seems to be similar (Vines et al., 2014; Wicherts et al., 2006) or even slightly lower than observed in most previous studies that reported sharing rates for mainly raw data (Hardwicke and Ioannidis, 2018; Krawczyk and Reuben, 2012; Tedersoo et al., 2021; Vanpaemel et al., 2015). Additionally, in line with previous studies (Tedersoo et al., 2021; Vines et al., 2014), we found that the timespan between request and the publication date significantly influenced whether or not relevant information was sent ($\beta = -0.12, p = .01$), with a lower likelihood for older publications (OR = 0.89; Fig. 4). Although this contrasts with the aforementioned lack of a significant time-related modulation observed for the overall response rate to our initial e-mail, it indicates that the amount of time past from publication to request is an important factor for the success of such requests after all. None of the other investigated factors (e-mail address, authorship position, complexity, COVID, reminder, personal acquaintance) significantly influenced information-sharing (see supplemental results).

Although our experience with contact requests to authors indicates that there is still room for improvement when it comes to information sharing in neuroimaging research, from a higher-level perspective we were overall quite successful with our approach. In fact, four out of seven meta-analytic projects of our own would not have been possible without the additional information obtained via requests due to having not enough studies required for a proper neuroimaging meta-analysis (>17 experiments), and two analyses would have had substantially lower statistical power. Only in one case we decided to change our approach because we did not manage to obtain enough data. Therefore, contacting study authors in the context of meta-analytic projects was quite a successful strategy despite the limited response rates.

3.2.2. *Possible reasons for why authors do not share information*

Given that the information-sharing rates we observed were similar to those of previous studies asking for raw data, legal issues and other expected disadvantages appear not to be the main reasons behind a lack of information sharing. In fact, in most of the responses, study authors declared that they did not have (access to) the data anymore or could no longer find it, redirected us to a co-author, or said that they would have a closer look or would send data later but never did (Fig. 1). Thus, the main obstacles seem to lie in data management and time issues.

Research data management (RDM) is a crucial part of scientific research, which, unfortunately, often does not receive enough attention. While almost every scientist appears to be aware of the necessity and benefits of appropriate RDM (Wilms et al., 2020), the responses of authors to our requests indicate that good RDM has not yet fully made its way into neuroimaging research. Especially given the space-taking and complex nature of neuroimaging data, it is of utmost importance that these are stored, properly backed-up, documented and, by doing so, made easily findable and accessible for oneself but also for other researchers, as proposed in the FAIR principles of RDM (Wilkinson et al., 2016). This is not only true for data/results that are published, but also for data that end up not being published within the project/contract timeline. However, storing the data is only half the work: the data, much like the analysis pipelines, must be properly structured, organized and annotated so that anyone, including the original authors themselves, can reuse them in the future. If this is not done in time after finishing the project, the data will be most likely lost for effective future use.

One factor determining RDM strategies and, in turn, the time authors are willing to invest in finding, retrieving, and potentially re-analyzing requested data from the past is the incentive structure in academia, which entails a strong pressure for publications (Miller et al., 2011), especially at early career stages (Everett and Earp, 2015). This pressure works against practices of proper RDM and sharing by setting a high priority on publishing several works without necessarily taking care of data sharing ("publish or perish", Miller et al., 2011), or not rewarding these important but time-consuming practices when it comes to receiving funding (Houtkoop et al., 2018). Much can thus be (and is already) done at the level of the academic system in terms of incentives, financial, career and technical support, as well as at the lab culture level to promote better RDM practices (Kohrs et al., 2023). Likewise, at the educational level, it is important to introduce the topics of reproducibility and replicability, open science, and proper data management/documentation as early as possible, to sensitize future researchers to these issues and increase their awareness of existing resources (Everett and Earp, 2015; Klingner et al., 2023; Kohrs et al., 2023). This could increase the perceived competence in RDM and data sharing and, in combination with changing incentives at the system level, pave the way to a wide-spread adoption of open-science practices (Klingner et al., 2023). Furthermore, a good practice for planning a research project would be to explicitly include a data-aftercare phase, regardless of whether the data are planned to be published. Currently, many research

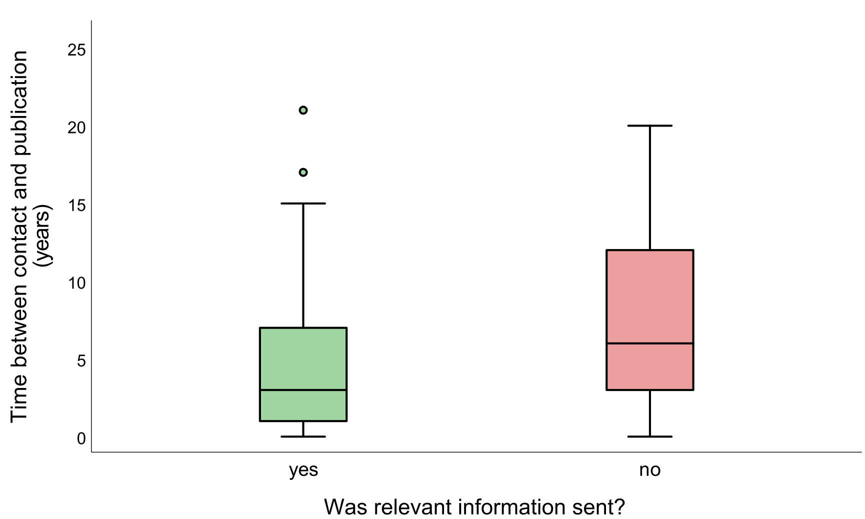

Fig. 4. Time span between request and publication as a function of whether relevant information was sent.

funding agencies already require such a “data handling” plan for grant proposals, but often this plan is provided without specifically reserving any extra time for this task.

Over the last few years, many tools have been developed with the aim to facilitate good RDM practices for neuroimaging research (Niso et al., 2022). These include resources for sharing or organizing data or code associated with publications such as Neurovault (https://neurovault.org/) (Gorgolewski et al., 2015), the Chinese Color Nest Data Community (https://ccndc.scidb.cn/en/) (Liu et al., 2021), Open Science Framework (https://osf.io), Open Neuro (https://openneuro.org/) (Markiewicz et al., 2021), ANIMA (https://anima.fz-juelich.de/) (Reid et al., 2016), Brainlife (https://brainlife.io/about/)(Hayashi et al., 2024), Datalad (https://www.datalad.org/)(Halchenko et al., 2021), GIN (https://gin.g-node.org/); FigShare (https://figshare.com), zenodo (https://zenodo.org/), or NeuroLibre (https://neurolibre.org/) (Karakuzu et al., 2022). Other tools like ARIADNE (https://igor-biodgps.github.io/ARIADNE/graph/graph.html)(Hartmann et al., 2023) have been developed to navigate through all these resources. The possibility to share data and code at the time of creation/publication offered by these platforms is valuable and can greatly increase the chance of re-using data directly, without the need to contact the authors of a given study. However, for meta-analytic studies, and possibly also other follow-up work, the results of interest often are not the immediate study results and data available from such platforms but rather (potential) results from analyses beyond the main focus of the original investigation (for instance (Küppers et al., 2024) where contrasts of the control condition versus baseline were needed). Making certain results of a publication openly available is, therefore, often not the end of the journey. When approaching the end of a study or funding period, scientists should ask themselves the question: How prepared am I for a data-sharing request or for providing detailed information on the study?

3.3. Limitations

Our considerations are primarily based on types of data and requests that are important for meta-analytical studies in neuroimaging research. While this narrows our focus, it still showcases important general issues that are applicable to the broader field of natural sciences in which the amount and complexity of collected data keep increasing, as does the need for replication and data reuse. An additional limitation is the retrospective nature of the current work, relying on data from requests to authors not randomly selected and, therfore, without the chance to achieve a representative sample of authors. Furthermore, the requests were just sent from members or collaborators of a single research institute. This might have introduced some bias in the data and results. However, given that response and information sharing rates are similar as those of previous studies, we assume the effect of sampling bias to be minor. Further, when interpreting the response rates we observed it needs to be considered that not receiving a response could be due to several reasons: (i) the author read the e-mail but did not reply, (ii) the e-mail was labeled as junk and was never read, or (iii) the e-mail address did not exist anymore but no delivery failure message was sent (or a failed-delivery e-mail was mislabeled as junk and went unnoticed). We cannot distinguish between these reasons, and all these instances were categorized as “unanswered request”, making this category somewhat heterogeneous and precluding a clear-cut interpretation. Finally, across our various meta-analytic projects, the reminder policy was not fully equivalent. That is, in some projects all unanswered requests were followed up by a reminder; in others, only those authors who had initially replied that they would send data received a reminder; and for yet others, only one request was sent in any case. This diversity is due to the retrospective nature of the current study and might explain differences to previous contact request studies, where emails and reminders were sent in a more consistent fashion.

4. Conclusion

Although we experienced difficulties and failures when contacting authors for information in the context of meta-analytic studies, our overall approach was rather successful. Thus, despite the limited rate of relevant responses, we think it is still worthwhile to contact authors for unpublished results and additional information to make some projects fly. Yet, there is quite some room for improvement regarding authors’ responses and the rates of sharing information to make such requests even more effective. In our view, this strongly argues for several changes in academic publishing systems: On the one hand, this concerns pragmatic details such as the decision of whom to assign the role of a corresponding author and which email address to use. On the other hand, this concerns the tradeoff between comprehensiveness and conciseness of scientific reports. For instance, in publications of neuroimaging experiments, behavioral data should receive the same consideration as neuroimaging data do, and available reporting guidelines for a given field or method should be followed. Most importantly, though, scientists should be better prepared and equipped for efficiently answering requests and questions regarding their published work, beyond the sharing of raw data and analysis code. This preparation is strongly facilitated by an adequate RDM strategy, making it much more likely that valuable data remain available for re-use or follow-up analysis. For this change to happen at a large scale, however, a more profound system-level change of the incentive structure in academia is needed.

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Declaration of Competing Interest

The authors declare no potential conflict of interest

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.neubiorev.2026.106693.

Data Availability

Data and analysis code of the empirical part can be found online: https://osf.io/43nra/?view_only=680711dc4f1b45439e615d8defb19076

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