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A registered report survey of open research practices in psychology departments in the UK and Ireland

Priya Silverstein[1,2] | **Charlotte R. Pennington**[3] | **Peter Branney**[4] | **Daryl B. O'Connor**[5] | **Emma Lawlor**[6] | **Emer O'Brien**[6] | **Dermot Lynott**[6]

[1]Psychology Department, Ashland University, Ashland, OR, USA

[2]Institute for Globally Distributed Open Research and Education, Gothenburg, Sweden

[3]School of Psychology, Aston University, Birmingham, UK

[4]School of Social Sciences, University of Bradford, Bradford, UK

[5]School of Psychology, University of Leeds, Leeds, UK

[6]Department of Psychology, Maynooth University, Maynooth, Ireland

Correspondence
Dermot Lynott, Maynooth University, Mariavilla, Maynooth, County Kildare, Ireland.
Email: dermot.lynott@mu.ie

Funding information
Aston University

Abstract

Open research practices seek to enhance the transparency and reproducibility of research. While there is evidence of increased uptake in these practices, such as study preregistration and open data, facilitated by new infrastructure and policies, little research has assessed general uptake of such practices across psychology university researchers. The current study estimates psychologists' level of engagement in open research practices across universities in the United Kingdom and Ireland, while also assessing possible explanatory factors that may impact their engagement. Data were collected from 602 psychology researchers in the United Kingdom and Ireland on the extent to which they have implemented various practices (e.g., use of preprints, preregistration, open data, open materials). Here we present the summarized descriptive results, as well as considering differences between various categories of researcher (e.g., career stage, subdiscipline, methodology), and examining the relationship between researcher's practices and their self-reported capability, opportunity, and motivation (COM-B) to engage in open research practices. Results show that while there is considerable variability in engagement of open research practices, differences across career stage and subdiscipline of psychology are small by comparison. We observed consistent differences according to respondent's research methodology and based on the presence of institutional support for open research. COM-B dimensions were collectively significant predictors of engagement in open research, with automatic motivation emerging as a consistently strong predictor. We discuss these findings, outline some of the challenges experienced in this study, and offer suggestions and recommendations for future research. Estimating the prevalence of responsible research practices is important to assess sustained behaviour change in research reform, tailor educational training initiatives, and to understand potential factors that might impact engagement.

KEYWORDS

credibility revolution, open science practices, replication crisis, researcher engagement, responsible research practices

PROBLEMS FOR SCIENCE AND PSYCHOLOGY

It is widely accepted that there is a replication crisis in psychology (De Boeck & Jeon, 2018; Giner-Sorolla, 2019; Maxwell et al., 2015; Munafò et al., 2017; Pashler & Wagenmakers, 2012). It has been estimated that up to 60% of findings in psychology cannot be replicated (Klein et al., 2018; Open Science Collaboration, 2015), and these replication failures cannot seemingly be explained by simple methodological or sample differences (Ebersole et al., 2016; Klein et al., 2018). By now, evaluations of replicability have been conducted across a range of disciplines, from economics (Camerer et al., 2016) and experimental philosophy (Cova et al., 2021) to cardiovascular health (Prinz et al., 2011) and cancer biology (Begley & Ellis, 2012; Errington et al., 2021), reporting wide variability in 'successful' replications (30%–90%). These studies, and the relatively low rates of replication, have resurfaced a plethora of problematic issues that seem to permeate the scientific literature, including *p*-hacking, selective reporting, hypothesizing after the results are known (HARKing), and publication bias (Ioannidis, 2005; Kerr, 1998; Rosenthal, 1979; Simmons et al., 2011). Acknowledging the existence of these problems has led to a focus on the concept of 'questionable research practices' (QRPs) and attempts to estimate their prevalence in psychology (John et al., 2012). While QRPs may not be considered as outright fraud and may reflect previously well-established research norms, they occupy a grey area in terms of research integrity and certainly fall well short of idealized views of how researchers should behave (Merton, 1942; Ritchie, 2020).

In this paper, rather than revisiting and enumerating QRPs, we focus instead on the positive behaviours that psychology researchers engage in – termed *responsible research practices* (RRPs; Gopalakrishna et al., 2022) – that serve to enhance the transparency, rigour and reproducibility of scientific findings. To understand the level of engagement with RRPs, and consider some factors that may impact engagement, we conducted a large-scale survey-based study targeting psychologists conducting research in the United Kingdom or Ireland. In recent years, both countries have seen major pushes for increases in open research practices (e.g., via the Research Excellence Framework www.ref.ac.uk, UK Reproducibility Network www.ukrn.org, and National Open Research Framework www.norf.ie), although to date there is little in the way of discipline-specific survey data that quantifies the extent of researcher engagement. We provide descriptives of the overall levels of engagement for a range of RRPs and conducted a series of exploratory regression analyses to examine which factors are most strongly associated with higher levels of engagement.

We first review some recent studies examining the level of engagement in RRPs, before outlining the benefits of discipline-specific surveys and our specific focus on psychology. Finally, in viewing science as behaviour (Norris & O'Connor, 2019; O'Connor, 2021), and taking inspiration from the COM-B model of behaviour change, we consider specific factors related to capabilities, opportunities, and motivations, that may impact researcher engagement in open research practices.

Recent work on responsible research practices

Two recent national studies on open research – Gopalakrishna et al. (2022) and Norris et al. (2022) – investigated both the prevalence of RRPs and considered a range of possible explanatory variables. Gopalakrishna and colleagues conducted a survey of researchers based in the Netherlands, finding large differences of engagement in various practices. For example, the most commonly incorporated practices included 'disclosing conflicts of interest' (96.5%) and 'avoiding plagiarism' (99.0%), while the least common practices included 'preregistration of study protocols' (42.8%) and 'keeping comprehensive research records' (56.3%).

Gopalakrishna and colleagues also found differences in engagement based on academic discipline, academic rank, researcher gender, and research methodology. Specifically, researchers in life sciences and medicine showed more engagement in RRPs than those in the social and behavioural sciences; associate professors and professors were more engaged in RRPs than assistant professors and post-doctoral researchers; male researchers engaged in more RRPs than female researchers; and researchers employing non-empirical research methods engaged in fewer RRPs than those engaged in empirical research.

In considering what factors might be related to the extent of researcher engagement in RRPs, Gopalakrishna et al. found that increased publication pressure was related to lower engagement, whereas mentoring, funding pressure from institutions, scientific norm subscription, likelihood of questionable research practice detection by collaborators, and work pressure were all positively related to engagement in RRPs.

In the United Kingdom, Norris et al. (2022) similarly found large differences in engagement depending on the specific practice, ranging from 77.8% of researchers pursuing open-access publishing, down to 8.7% of researchers submitting a Registered Report journal format. Norris et al. also found a disconnect between researcher awareness of specific practices and their actual implementation of these practices, with respondents highlighting improved incentives, dedicated funding, and appropriate recognition in promotion and recruitment criteria as factors that would help them engage further with open research.

Both of the above studies take a broad approach, examining uptake of RRPs across a range of disciplines, albeit with differing levels of granularity. This means that the number of researchers surveyed for any given discipline is relatively small, and it may be difficult to generalize from these samples to disciplines as a whole. For example, responses to the Norris et al. survey (2022), with 1274 participants, included data from 216 psychology researchers, representing 17% of the total sample, and an estimated 1% to 2% of psychology researchers in the United Kingdom. In addition, Norris et al.'s work explicitly targeted institutions that were currently members of the UK Reproducibility Network (https://www.ukrn.org/), a group which promotes and fosters open research practices, which means those institutions are likely to be more engaged with open research practices than non-member institutions, possibly leading to reported engagement rates that are higher than the norm. It is likely that the disciplinary differences observed in these studies emerge from researchers from different disciplines having differing priorities, differing concerns regarding the replication crisis, combined with different capabilities, opportunities, and motivations for engaging in RRPs. Furthermore, researcher behaviour varies not just across disciplines but within disciplines, too; studies show that in subdisciplines of psychology, there can be wide variability in how researchers engage with RRPs, as we discuss below.

Responsible research practices in psychology

Psychology researchers have played a major role both in recognizing and diagnosing the extent of replication and reproducibility issues in science (Open Science Collaboration, 2015; Simmons et al., 2011), while also being at the forefront in terms of generating potential solutions, whether pushing for enhanced reproducibility (Munafò et al., 2017), advocating for study preregistration (Nosek et al., 2018), or introducing Registered Reports to a wide range of the discipline's leading journals (Chambers & Tzavella, 2022).

Nonetheless, there are now several literature evaluation studies that have examined to what extent psychologists engage in specific RRPs. When looking at these practices in isolation, this research suggests a relatively low uptake, as well as variability across psychology subdisciplines. For example, Holcombe et al. (2019) note that for vision sciences, engagement in practices such as open data and open code is low. Towse et al. (2021) show that while data sharing is low across the board in psychology (at around 4%), data sharing in social psychology journals is higher than that observed for cognitive science or applied psychology journals. Rochios and Richmond (2022) show that data and material sharing in developmental psychology articles was lower than in cognitive psychology articles published in *Psychological Science*. However, at the moment there is little in the way of comparative data across psychology, and nothing that covers the full breadth of subdisciplines in psychology, something that we address in the current study.

As well as considering differences in engagement with RRPs within psychology, there are other reasons why discipline-specific surveys, rather than cross-disciplinary or discipline-agnostic studies, such as those of Gopalakrishna et al. and Norris et al. can be useful. First, focussing solely on psychology should enable us to reach a larger, more representative sample of researchers than has been achieved with previous studies. By focussing on all psychology departments, and psychologists working outside traditional psychology departments (e.g., in larger units of Social Sciences, or within Business and Management Schools), we aim to gain a fuller picture of the level of engagement within the discipline. Aiming for a larger sample than previous research will also make it easier to make comparisons between different groupings, for example, between subdisciplines of psychology, or between researchers at institutions that provide support via institutional leads for open research or open research working groups, compared to those institutions that do not (see also the work being conducted as part of the STORM project: https://osf.io/av4ky/).

A second advantage of focusing on a single discipline is that we can make more fine-grained distinctions in survey questions that are of relevance to researchers in psychology, but perhaps less relevant to those working in other fields. For example, where a more discipline-agnostic survey might probe engagement with study preregistration generally, we have incorporated more fine-grained questions that distinguish between sub-elements of the preregistration process, such as distinguishing between the preregistration of study hypotheses, designs, and analysis protocols. Each of these elements are important in their own right, and previously, data have not been presented that speak to whether researchers who are preregistering studies give equal weight to these distinct elements. Having this level of detail provides important information to help in identifying training needs or developing targeted policy interventions.

Third, in also identifying potential barriers to entry to RRPs, the survey helps identify areas of psychology or components of the research process where people may need additional support, training, or incentives, that will allow us to develop targeted ways to support researchers in RRPs and improve the credibility of psychological science more generally.

In sum, psychology, as a discipline, has been at the centre of discussions of the replication and reproducibility crisis and has been one of the areas leading the way in terms of open research reform. However, in the wake of such endeavours, and despite major pushes to increase transparency and reproducibility, it remains unclear the extent to which psychologists specifically are engaging with RRPs, and whether their uptake is similar across subdisciplines of psychology.

Capability, opportunity, and motivation as explanatory factors for engagement in open research

Science is behaviour (Norris & O'Connor, 2019), and conducting transparent and replicable science requires researchers to enact many specific behaviours, several of which are at odds with historical scientific norms. With this in mind, we can look to the literature on behaviour change to theorize how to encourage individuals to increase their engagement in RRPs, and to identify potential barriers to such change. Behaviour change has been studied extensively with regard to facilitating healthy behaviours, such as reducing smoking (Armitage, 2008), alcohol consumption (Armitage & Arden, 2012), stress-induced eating (O'Connor et al., 2015), and increasing physical activity and healthy nutrition (Seppälä et al., 2017). Here, we apply the COM-B model (Cane et al., 2012; Michie et al., 2011) which is situated at the centre of the Behaviour Change Wheel (Michie et al., 2011) and provides a way of viewing potential influences on behaviour change. The COM-B framework proposes a 'behaviour system' involving three essential conditions for behaviour change: *capability, opportunity*, and *motivation*. These three pillars of the model can be further subdivided, with Capability referring to both an individual's *psychological* and *physical* ability to participate in an activity. Opportunity refers to external factors, *social* or *physical*, that make a behaviour possible. And lastly, motivation refers to the conscious (*reflective motivation*) and unconscious (*automatic motivation*) cognitive processes that direct and inspire behaviour.

While the COM-B model has been applied successfully to a range of health-related areas, Norris and O'Connor (2019) explicitly raise the possibility of applying this behaviour change approach to promote the uptake of open research practices. Specifically, they applied the Behaviour Change Wheel approach to help understand how open research practices may be identified, how barriers towards these behaviours may be tackled, and how interventions can be developed to increase RRPs. Moreover, the barriers and facilitators were mapped onto the COM-B model. In other words, how could a researcher's capabilities, opportunities, and motivations affect the likelihood that they will engage with responsible research practices?

Indeed, in the recent survey by Norris et al. (2022), certain elements of the COM-B model relating to opportunity and capability were especially relevant to future possible engagement in RRPs. For example, 'Incentives from funders, institutions or other regulators', and 'Recognition of Open Research in promotion and recruitment criteria' were prominent examples of researchers citing *social opportunities* impacting their future engagement. 'More training using Open Research practices' and 'More information on Open Research practices' were highlighted as aspects of *psychological capability* that were deemed important by many respondents.

The COM-B approach therefore allows us to consider both personal (e.g., psychological capability) and structural (e.g., social opportunity) factors that may impact the behaviours in question. This is an important aspect of the framework – since researchers do not exist in a scientific vacuum, we need to consider, for example, to what extent local norms or institutional support contribute to a researcher's level of engagement in open research behaviours. Do institutions provide increased capability (e.g., through offering department-level open research training), increased opportunity (e.g., through funding available to pay for open-access publication; or institutional incentives like open research awards, Merrett et al., 2021), and increased motivation (e.g., by promoting the advantages to researchers of RRPs)? And how do these features of the research environment impact on researcher behaviour (see Stewart et al., 2021)?

Goals of this survey

In the current survey, we asked psychologists working in Higher Education institutions about their engagement in RRPs that cut across the entire research process and explicitly asked them to consider factors related to their capability, opportunity, and motivation for engagement in open research. Answers to these questions provide a census on the degree of uptake of RRPs in psychology in the United Kingdom and Ireland and help to monitor progress and sustained behaviour change in open research, as well as assessing the need for tailored educational initiatives to increase uptake. Furthermore, applying the COM-B model in a discipline-specific manner aimed to provide insights into potential barriers and incentives, both systemic and individual, that impact on engagement with open research across psychology.

We hoped that a targeted drive for recruitment (e.g., contacting individual researchers directly) would result in a representative snapshot of open research behaviours by psychological scientists in the

United Kingdom and Ireland, reducing the possible bias towards only those actively engaging in open research behaviours (although self-selection bias is always likely to impact on survey responses to a certain extent). We also investigated possible explanatory factors using the COM-B model by assessing capability, opportunity, and motivation to engage in RRPs. This theoretically-driven framework allows us to consider open research through the lens of behaviour change.

METHOD

Ethical approval

This design follows the four principles in the British Psychological Society Code of Human Research Ethics (Oates et al., 2021). Briefly, this means it includes procedures to ensure valid consent were built into the online questionnaire and pre-emptive review was conducted by the Social Research Ethics Sub-Committee of Maynooth University (Ethics ID 2448789).

Participants

Participants were academics, researchers, and PhD students working in a unit with psychology in the title (e.g., Department/School of Psychology) or in the psychology subject area of a larger unit (e.g., School of Social Sciences) in a higher education institution in the United Kingdom or Ireland. All psychology researchers working at higher education institutions in the United Kingdom and Ireland were invited to participate. To be considered eligible, researchers had to perform, on average, at least 8 h of research-related activities per week (following Gopalakrishna et al., 2022), consider themselves a researcher in psychology, and be at any career stage from PhD level to full professor (i.e., including PhD candidate, junior researchers, postdoctoral researcher, lecturer, senior lecturer, assistant professor, research fellow, reader, associate, or full professor).

Design and procedure

This was a cross-sectional, web-based survey examining the notion of responsible research practices (RRPs) and the COM-B model. The survey was fully anonymized, and designed to allow participants be able to complete it in approximately 10 min. Researchers were contacted in one of two ways: either via individual emails or via email distribution lists (e.g., through contacting individual departments or heads of department to cascade the survey to researchers). Distribution lists were considered to be particularly important for accessing PhD students and non-faculty researchers, who are not always fully represented on university staff web pages. The email invitation contained details about the aims of the study and a direct link to participate. We aimed to have the survey open for 8 weeks and to send up to 3 reminder emails during this period. Once the 8-week period had elapsed, if we had not achieved a sample size of 2000 participants, we aimed to extend the survey window for 4 weeks, and also advertise via commonly used social media channels (e.g., Twitter, Mastodon). After this point we aimed to close the survey and terminate data collection.

Once a participant opened the survey, they were presented with an information page followed by a consent form. Following completion of the consent page, participants completed the screening questions (whether they spend at least 8 h per week on research activities, including supervision duties, and if they are based in the United Kingdom or Ireland). They then provided some demographic information on academic rank, psychology subdiscipline, and primary research methodology. If respondents indicated that they spend less than 8 h per week on research activities, they could proceed no further with the survey. Once this point was passed, the participant was free to complete the remainder of the survey.

Survey

The survey had five general components: participant information & informed consent, demographics and confirmation of researcher status, Responsible Research Practice Questionnaire (19 items – 15 items on researcher's general practices – see Tables 1, and 4 linked to first contact with open research), COM-B Questionnaire (14 items related to capability, opportunity, motivation – See Table 2), 3 short additional items (1 item relating to institutional support), 1 item on academic roles of influence (e.g., journal editor roles, member of grant funding panels), 1 open-text question for general comments, and a final debrief. Following the debrief, participants were asked if they would like to be entered into a draw to win one of 50 £20 gift vouchers and, if they chose, were directed to a separate survey page to provide their email address. In this way, participant contact details were never linked with survey responses. The full set of survey questions can be found in Appendix A and on the OSF project page (https://osf.io/xjby2/).

The questions on RRPs and explanatory variables were generated to cover the complete research cycle of a psychologist, taking into account study design, data collection, analysis, publishing, sharing of data/code/materials, and conflicts of interest. All authors were involved in iteratively developing the questions until the final set and phrasings for each were agreed. All 15 questions on RRPs have a 7-point Likert scale ranging from 1 = Never to 7 = Always, in addition to a 'Not Applicable' option. Following this, four questions assess researcher's first contact with open research (i.e., when they first engaged

TABLE 1 Statements regarding responsible research practices.

Component of the research process	Statement
Conflicts of interest	I always disclose who funded my studies and all my relevant financial and non-financial interests in my publications
Open materials	I deposit my study materials and stimuli on a publicly accessible repository
Open data	I contribute, where appropriate, to making my research data findable, accessible, interoperable and reusable in accordance with FAIR principles
	I deposit the raw anonymized data, and processed data (used for reported analyses) on a publicly accessible repository OR, where data anonymization is not possible, I deposit my identifiable raw and processed data in a controlled archive that provides access to future researchers
Open analysis and code	I deposit analysis scripts, analysis code, or statistical output files on a publicly accessible repository
	I deposit source code for any computational research (e.g., neural networks, machine learning, cognitive architectures etc.) on a publicly accessible repository
Study preregistration	I preregister my study hypotheses and make them available on a publicly accessible repository (e.g., AsPredicted, OSF etc.)
	I preregister study designs/protocols and make them accessible on a publicly accessible repository
	I preregister analysis plans and make them available on a publicly accessible repository
	I preregister analysis code or scripts (e.g., R code, syntax files), and make them available on a publicly accessible repository
	I submit manuscripts for publication as Registered Reports (i.e., where the manuscript is reviewed, and may receive in-principle acceptance, prior to data collection and analysis)
Dissemination and review	I make my academic manuscripts freely available prior to publication, for example via a preprint repository (e.g., PsyArXiv, BioArxiv, OSF Preprints etc.), personal web page or other fully open online repository
	I publish my work in open-access journals
	I sign my reviews when peer-reviewing manuscripts
	I share slides from my research talks on a publicly available repository or agree to have a research talk I've given made publicly available (e.g., via YouTube or other online platform)

TABLE 2 The statements used in the survey relating to the COM-B model for behaviour change.

COM-B Dimension	Statement
Physical capability	I am physically capable of engaging in open research practices (e.g., I have sufficient physical stamina, I have sufficient physical skills)
Psychological capability	I am equipped with the skills necessary to engage with open research practices
	I have enough information and training on open research practices
Physical opportunity	I have access to the appropriate research infrastructure to engage in open research practices (e.g., access to appropriate repositories, computing resources etc.)
	I have enough time to implement open research practices in my work
	I have sufficient financial support to engage in open research (e.g., to cover costs of video recordings, transcription/translation, data storage etc.)
Social opportunity	Others in my wider research environment engage with and encourage the use of open research practices
	There are adequate incentives from funders, institutions or other regulators to engage in open research
	There is sufficient recognition of open research in promotion and recruitment criteria
Reflective motivation	I am sufficiently motivated to engage with open research practices
	I believe open research practices to be a positive thing
	I consciously plan on working more with open research practices in the future
Automatic motivation	I have developed the habit of engaging in open research practices as an everyday part of my research process
	When I think about my research, I automatically think about the open research elements as well

Note: These statements relate to capability (C), opportunity (O), and motivation (M) as three key factors or elements linked with changing behaviour (B). Capability refers to an individual's psychological and physical ability to participate in an activity. Opportunity refers to external factors that make a behaviour possible. Lastly, motivation refers to the conscious and unconscious cognitive processes that direct and inspire behaviour.

with any of the RRP questions mentioned, providing a year, or N/A response), and whether they had specifically been involved in study preregistration, submitted a Registered Report, or been involved in a large-scale, multi-site study (involving a replication or original research). The latter three questions have Yes/No (and N/A) responses.

The questions on explanatory factors were generated based on the COM-B approach to behaviour change, and also drew on existing surveys by Keyworth et al. (2020), Norris et al. (2022), and Osborne and Norris (2022). Unlike previous surveys, we included statements relating to all 6 elements of the COM-B approach: physical and psychological capability, physical and social opportunity, and reflective and automatic motivation. Briefly, Capability questions refer to an individual's psychological and physical ability to participate in an activity. Opportunity questions relate to external factors that make a behaviour possible, such as having sufficient opportunities to engage in open research, and whether open research practices are considered normative in their wider research environment. Lastly, Motivation questions relate to the conscious and unconscious cognitive processes that direct and inspire behaviour, such as the extent to which respondents feel personally motivated to engage in RRPs, and the extent to which they have automatized the inclusion of RRPs in their research process. These questions are focussed on the individual researcher and their environment at the current point in time, rather than for example highlighting areas that they would like to see improvements in the future (see Norris et al., 2022). As with the research practice questions, participants provided a rating on a 1–7 scale, which provided a more fine-grained picture than utilizing binary responses. A rating of 1 means 'strongly disagree' with the statement, while a rating of 7 means that you 'strongly agree'. See Table 2 for a list of these statements.

We included one question on roles of influence that academics may occupy as part of their academic service duties (e.g., journal editors, members of grant review panels). It is possible that those occupying such roles may exert more influence on research practices in their wider community than those who do not occupy roles of influence. One further question tapped into broader institutional support, assessing whether the respondent's department or university has a local open research working group, or whether there is an institutional lead for open research, either of which would signal higher-level support from the institution for open research approaches generally (Yes/No/Don't Know response). Finally, respondents were provided with an open text box to provide any additional information regarding open research generally, or regarding benefits/challenges to engaging with open research practices. Analysis of responses in the open text box was not planned for the current study, but may be analysed at a future point. In this event, a separate analysis plan will be developed. Qualtrics survey files are available on the project's OSF page (https://osf.io/kpqnc/).

Data processing and statistical analysis

The preregistered analysis plan (see Appendix B for full details, also available at https://osf.io/waet9/) was based on that of Gopalakrishna et al. (2022) for the Dutch National Survey of Research Practices. By and large, we were able to follow our research plan as outlined in the Stage 1 submission, although we made some minor changes to the wording of some questions, with editorial approval, which are documented in the Change Log in the Supporting Information (https://osf.io/246tx). However, we did need to make some adjustments to our data pre-processing plan, which were discussed with the editor prior to implementing, and prior to conducting any of our preregistered analyses (see Table 1, for changes marked with a *). The reasons for these changes were mainly due to problems with surveys completed via social media links, which we summarize below as they may have relevance for many psychology researchers who recruit participants in this fashion.

Despite emailing researchers directly and using professional contacts such as the Association of Heads of Departments of Psychology, and receiving endorsements from both the British Psychological Society and the Psychological Society of Ireland, we found that recruitment was slow. We decided that we would opt to share the survey through social media channels in order to reach our target of ~2000 respondents. When we stopped data collection, we had over 2300 respondents. However, when we started to collate the data we noticed some odd patterns, specifically in the data that was collected from social media platforms. When we released the survey via social media, we created a duplicate of the original survey and added an additional attention check question as we were aware from other research (Hays et al., 2023) that bots and trolls could impact data quality. The attention check simply asked participants to indicate if they had recently been on a trip to Mars, with those that failed this deemed to have been inattentive and their data removed prior to analysis. However, in these planning stages, we did not predict the extent of the problem.

Initially, we saw that over 35% of respondents in the social media version of the survey had failed the attention check. So, the attention check was doing its job, but this seemed rather high. Even after filtering incomplete surveys, attention check failures etc., a lot of the remaining data from the social media survey consisted of what we term *suspicious responders*. Examining the data more closely, we realized that these suspicious responders were most likely from bots that pick up survey links automatically on social media and autocomplete surveys. What's more, the bots also appear to use tools like ChatGPT to complete open text boxes, giving superficially relevant sounding responses, which might be missed in the absence of careful checking (see example below). In light of these patterns, we decided to code all survey responses and found that these suspicious responders occurred with multiple red flags, including the following:

- responding from outside United Kingdom /Ireland, despite the fact that working in the United Kingdom /Ireland was a requirement for participation.
- tranches of responses that started at the same time and were completed within seconds of each other, suggesting some form of automation.

- peculiar rating patterns, especially with very low variance, and generally considerably lower variance than verified genuine responses.
- responses from institutions starting with the letters A, B, C or D, leading to a preponderance of responses from Abertay, Anglia Ruskin, Bishop Grosseteste, Brunel, Cardiff Metropolitan, City University, and similar. Of course, we expect some responses from these institutions, but they were considerably overrepresented compared to the others and importantly only in the social media version of the survey. We suspect the bots were randomly selecting options A, B, C, and D, and so were much less likely to select institutions beginning with other letters.
- inconsistent responses, such as indicating they were a PhD student in one place, but also a member of senior university management later in the survey, or indicating that they complete preregistrations all the time, but later saying they have never completed a preregistration.
- providing short, incongruent, irrelevant, or superficially relevant responses in open text boxes. For example, in an open comment box, the following was submitted: 'Interdisciplinary collaboration: Open research encourages collaboration between experts and researchers from different fields. This cross-cutting collaboration can lead to new ways of thinking and approaches that facilitate innovation'. The comment might seem reasonable, if a bit generic, but the same comment was entered from multiple respondents, indicating non-genuine, potentially automated, responses.

While each feature listed above might not be enough in isolation to judge a responder as suspicious, when several of them co-occur it is difficult to ignore. In this way, we treated surveys that contained two or more of the above features as suspicious responders and excluded them from further analysis. For the full dataset, after attention checks and all other filters had been applied, 615 (50%) of the remaining responses were still classed as suspicious responders. Ultimately, this meant that less than 6% of responses from the social media version of the survey were included in the final dataset, while only a single response from the non-social media survey was classified as a suspicious responder. This highlights the usefulness of having separate links for different recruitment approaches; otherwise, it may have been impossible for us to spot these issues. Once all data had been cleaned and validated, with a final sample size of 602 participants, we achieved 90% power to detect effect sizes of $r > .177$ with alpha set at .05 for regression analyses with up to 8 predictors, or effect sizes of $r > .131$ for analyses with a single predictor (G*Power, Version: 3.9.1.6; Faul et al., 2009. See Appendix C for our a priori power calculations for a range of effect sizes, Table A1). Table 3 shows how survey responses were processed, and the number of responses removed at each stage of pre-processing.

We describe below the remaining pre-processing of the data, calculation of descriptives and general trends in the data, and finally the planned series of regression analyses that examine which factors are most strongly associated with open research practices.

Our approach to pre-processing the data was heavily informed by the work on the Dutch National Survey by Gopalakrishna et al. (2022), but there are some notable exceptions. For example, because there are no subgroups in the present study (and all participants answered all questions), data analysis did not involve any imputation or missingness analysis. Following Gopalakrisha et al. there are no item non-responses; participants were required to answer and continue with the next questions or to withdraw from the survey. Although this approach removes the possibility of missing values, one must acknowledge that such decisions may impact the quality of the collected data. For a majority of questions, participants may respond N/A if the question does not apply to them. There may be various reasons for N/A responses, but whatever these reasons, an N/A indicates that this behaviour has not been performed.

For any responsible researcher practice questions where N/A is a viable answer, 'not applicable' were replaced by the lowest value of 1 ('Never') (see Gopalakrishna et al., 2022). This implies that we interpret 'NA' on these items as 'behaviour has not been performed' lumping possible reasons together. For COM-B explanatory factor questions, if an N/A response was selected, these values were replaced by the midpoint value of the scale. This implies that we interpret 'NA' on these items as indicating that the respondent neither agreed nor disagreed with the statement. Responses to the

TABLE 3 Summary survey response screening, until arriving at a final set of valid survey responses.

Total survey responses	2366
Number exiting from survey landing page, providing no responses	63 (2.7%)
Number not providing informed consent	84 (3.6%)
Number providing informed consent, but no further responses	30 (1.3)
Number not completing >8 h research (inclusion criteria)	90 (3.8%)
Number exiting before country question	9 (0.4%)
Number not responding from United Kingdom or Ireland (i.e., responded 'other')	29 (1.2%)
Number exiting before completing the survey	170 (7.2%)
Number failing Mars attention check*	442 (18.7%)
Number producing aberrant response patterns	22 (0.9%)
Number with mismatched country and university*	210 (8.9%)
Number with other suspicious responses* (e.g., tranche of responses starting and ending at the same time)	615 (26.0%)
Remaining Valid Responses	602 (25.4%)

Note: % Values are rounded to one decimal point. Items marked with * were not included in our original Stage 1 Registered Report but were deemed necessary to accurately filter out invalid responses.

TABLE 4 Demographics of the respondents by academic rank.

Academic rank	*N*	%
Assistant professor/lecturer	152	25.249
Associate Professor, Senior Lecturer, Reader or Professor	240	39.867
Other	8	1.329
PhD student or junior researcher	128	21.262
Postdoctoral researcher	49	8.140
Research Fellow/Senior Research Associate	25	4.153
Missing	0	0.000
Total	602	100.000

question on academic roles of influence were re-coded as binary, where 0 = 'no roles of influence', and 1 = 'at least one role of influence'.

If a survey was incomplete, either through technical error or through a participant withdrawing from the study, partial data were not included in any subsequent analyses. Similarly, if participants showed aberrant response patterns (e.g., the same ratings for all questions), or if the time taken to complete the survey was more than 60 min (which is approximately 4–5 times longer than it should take), those responses were excluded from analysis.

For descriptive analyses, for each research practice question (Qs 1–15) we calculate the mean, standard deviation, 95% confidence intervals, and overall prevalence. Prevalence reflects the percentage of responses that are 5, 6, or 7 on the Likert rating scale (e.g., 73% engage in the practice of study preregistration). For first contact with open research practices (Qs 16–19), we report the percentage of 'Yes' responses. For COM-B and additional explanatory questions (Qs 20–33), we report the mean scores, standard deviations, and 95% confidence intervals for each. For all descriptives, we also report means broken down by subdiscipline, academic rank and gender. Second, we assess the relationships between the measures (Qs 1–33), generating a Pearson's correlation matrix between all scale variables. Previous work in this area (e.g., findings from Gopalakrishna et al., 2022; Norris et al., 2022) has not reported full correlation matrices across research practices, and therefore, we didn't have clear expectations as to whether we would see consistent correlations across practices, or whether we would see more variability in correlations, perhaps reflecting researchers taking a more 'buffet' style approach (Bergmann, 2023) to open research, selecting particular RRPs, but not others.

For regression analyses, independent variables are the 6 explanatory variables from the COM-B component of the survey (reflecting physical/psychological capability, physical/social opportunity, reflective/automatic motivation). Mean scores were calculated for each participant for each of the 6 elements. All independent variables were mean centred prior to analysis, and all multiple regression models contain a base set of background variables dummy coded for subdiscipline, academic rank, gender, and research methodology. These background variables were entered simultaneously into the regression model, prior to the addition of explanatory variables or interactions.

All interaction models contain the separate variables that make up the interactions. We also conducted further exploratory analyses to consider the effect of Country (United Kingdom, Ireland), University type (e.g., Russell Group vs. Non-Russell group), and institutional support (i.e., whether there are local/institutional open research leads). Regression models estimate the impact of each of the explanatory predictors individually in separate regression models, and then simultaneously as a single regression model for each of the dependent measures. Linear regression analyses were performed on the primary dependent measure of Responsible Research Practice mean, with further binary logistic regressions examining participation in specific practices: preregistration, Registered Reports, and large-scale/multi-lab studies.

RESULTS

Descriptives

Table 4 summarizes demographics according to academic rank and gender of participants. Overall, we analysed valid responses from 602 individuals, which includes data from the United Kingdom (N = 505, 83.9%) and Ireland (N = 97, 16.1%), covering 111 different institutions, and giving an estimated response rate of approximately 6%. There is a reasonable spread of responses across career stages, with 21.3% representing PhD students, 12.3% Postdoctoral Researchers and Research Fellows, 25.2% Assistant Professors, and 39.9% Associate Professors or more senior academics (see Table 4). 60.6% of respondents were female, with 36.7% male, and 2.7% of respondents not selecting male or female categories or preferring not to say. A range of disciplines are represented, with reasonably large numbers from Cognitive, Developmental, Health and Social Psychology (Table 5). There are a low number of responses from the areas of Sport Psychology, Counselling Psychology and Personality Psychology in particular, so values related to those areas should be treated with caution since they can be easily skewed by outlier responses. The years people first engaged in the listed open research practices are shown in Figure 1, with a peak in 2018, but a wide range of responses.

Mean engagement scores (1 = Never, 7 = Always) (i.e., the mean rating for all 15 responsible research practices, excluding N/A responses) are summarized in Tables 6–13, by subdiscipline of Psychology (Table 6, see also Figure 2), research methodology (Table 7), academic rank (Table 8), gender (Table 9), country (Table 10), Russell Group status (Table 11), institutional support (Table 12), and academic roles of influence (Table 13).

Prevalence of responsible research practices

For each item, prevalence is calculated as the percentage of respondents who indicated ratings of 5, 6, or 7 on the Likert scale. Overall, we found that the level of engagement varied considerably across research practices (Figure 3, Table 14), from a low of 11.6% submitting Registered Report format articles to a high of 87.5% declaring any Conflicts of Interest. We see good engagement with open-access publishing, with 68.4% publishing in open-access journals and 48.5% posting preprints. Over

TABLE 5 Respondents per sub-discipline of psychology, sorted by increasing number in the overall sample.

Sub discipline	Frequency	%
Sports psychology	2	0.332
Counselling psychology	4	0.664
Personality psychology	7	1.163
Educational psychology	14	2.326
Forensic psychology	16	2.658
Neuropsychology	22	3.654
Organizational psychology	26	4.319
Clinical psychology	31	5.150
Biological psychology	32	5.316
Experimental psychology	45	7.475
Other	51	8.472
Health psychology	69	11.462
Developmental psychology	73	12.126
Social psychology	77	12.791
Cognitive psychology	133	22.093
Total	602	100.000

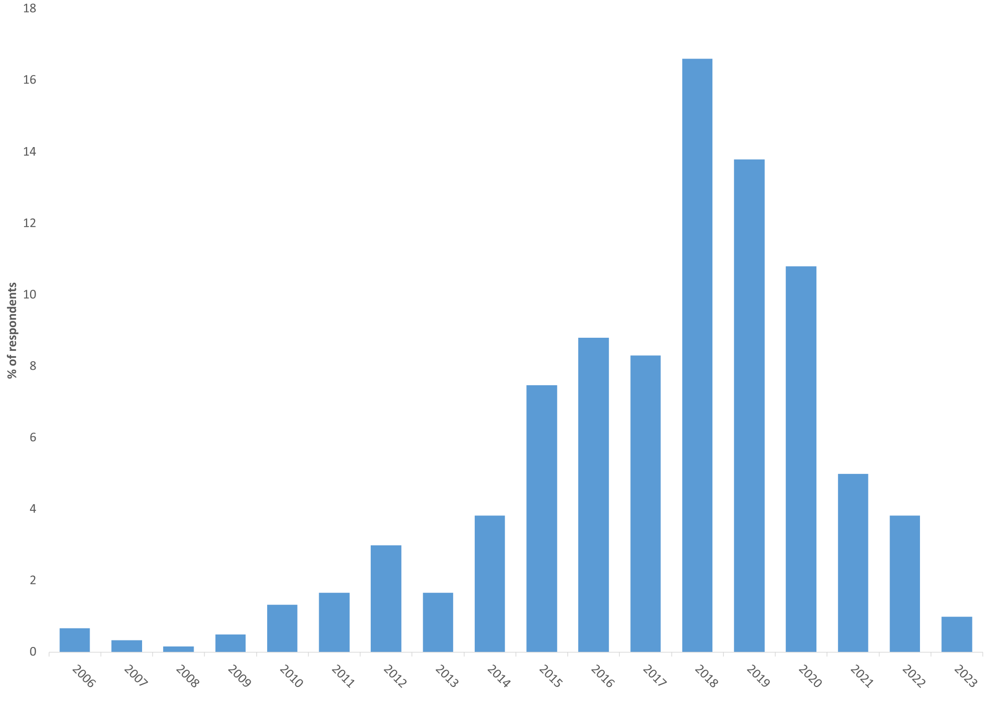

FIGURE 1 Summary of the year that respondents first engaged in one of the specified responsible research practices. Each bar represents the % of respondents from the overall sample. Responses included very small numbers of participants going back to as early as 1967, but we truncated the axis for visual clarity.

half of respondents reported that they share data in an open (53.2%) or FAIR compliant (67.8%) manner, while a majority (58.3%) also reported sharing materials. While a minority of respondents frequently preregister elements of their work, such as designs (47.5%), hypotheses (46.2%), and

TABLE 6 Overall mean engagement scores (1 = Never, 7 = Always) for subdisciplines of psychology, sorted by increasing level of engagement.

Subdiscipline	*N*	Mean	95% CI Upper	95% CI Lower	*SD*
Forensic psychology	16	3.653	4.104	3.201	0.922
Organizational psychology	26	3.719	4.253	3.185	1.388
Educational psychology	14	3.784	4.349	3.220	1.077
Clinical psychology	31	3.854	4.166	3.541	0.887
Other	51	3.918	4.279	3.557	1.314
Personality psychology	7	3.929	4.898	2.959	1.309
Health psychology	69	4.012	4.316	3.709	1.287
Neuropsychology	22	4.142	4.686	3.598	1.302
Developmental psychology	73	4.193	4.445	3.940	1.101
Experimental psychology	45	4.242	4.541	3.944	1.022
Biological psychology	32	4.251	4.587	3.914	0.972
Sports psychology	2	4.269	4.796	3.742	0.380
Social psychology	77	4.312	4.587	4.038	1.228
Cognitive psychology	133	4.456	4.655	4.258	1.169
Counselling psychology	4	4.921	5.734	4.108	0.830

Note: N/A values are not included in the calculation of means. $N = 602$.

analysis plans (45.5%), there is a much smaller proportion of researchers preregistering the actual analysis code or scripts run on the data (13.1%). About one-third (34.7%) of respondents reported sharing research talks (e.g., via YouTube, or sharing talk slides on an open repository), with lower numbers engaging in open peer review (24.4%), sharing open source (i.e., computational) code (19.6%), and submitting Registered Reports (11.6%). Table 15 shows the mean ratings for each open research practice. In the Supporting Information, we further break down the prevalence of each practice and mean ratings for each research practice by academic rank, sub-discipline of psychology, and preferred research methodology (see Supplemental Tables).

We also asked participants to provide a binary (Yes/No) response about their engagement with three specific research practices: preregistering a study, submitting a Registered Report article, and participating in a large-scale/multi-lab study, where we again see considerable variation (see Figure 4). When respondents were asked whether they had preregistered at least one study as the lead researcher, a majority (62%) responded Yes. When asked if they had submitted at least one Registered Report, a significant minority (29%) responded Yes. Finally, when asked if they have participated in at least one large-scale or multi-site study, again a minority (44%) responded Yes. Only a small percentage of respondents deemed these practices to be not applicable to their research (4%–5.1%).

For COM-B questions, Table 16 shows the mean scores (1 = Strongly Disagree, 7 = Strongly Agree) for each statement, and Table 17 provides the aggregate means for the six COM-B dimensions of physical capability, psychological capability, physical opportunity, social opportunity, reflective motivation, and automatic motivation. Considering the mean responses for the individual statements, respondents generally feel physically capable of engaging in open research, feel very positive about open research, and also plan on engaging more with open research in the future. By contrast, ratings are lowest for issues related to researcher resources (i.e., time available, having sufficient finances), as well as recognition and incentives for engaging in open research (i.e., whether open research is acknowledged in promotion criteria, or adequately incentivized by funders and institutions). While people generally felt they had the skills necessary to engage in open research, they did not necessarily have sufficient information and training on open research practices. In

TABLE 7 Overall mean engagement scores for each research methodology, sorted by increasing level of engagement.

			95% CI		
	N	Mean	Upper	Lower	*SD*
Mixed methods	143	4.009	4.221	3.796	1.296
Qualitative	42	4.087	4.516	3.657	1.420
Quantitative	417	4.230	4.337	4.123	1.110

Note: N/A values are not included in the calculation of means.

TABLE 8 Overall mean engagement scores (1 = Never, 7 = Always) for each academic rank, sorted by increasing level of engagement.

			95% CI		
	N	Mean	Upper	Lower	*SD*
Assistant Professor/Lecturer	152	4.081	4.258	3.903	1.115
Associate Professor, Senior Lecturer, Reader or Professor	240	4.106	4.240	3.972	1.059
Research Fellow/Senior Research Associate	25	4.170	4.549	3.791	0.966
PhD student or junior researcher	128	4.286	4.550	4.021	1.525
Postdoctoral researcher	49	4.316	4.588	4.045	0.970
Other	8	4.862	5.761	3.964	1.297

Note: N/A values are not included in the calculation of means. $N = 602$.

TABLE 9 Overall mean engagement scores (1 = Never, 7 = Always) for each gender, sorted by increasing level of engagement.

			95% CI		
	N	Mean	Upper	Lower	*SD*
Female	365	4.066	4.195	3.937	1.254
Non-binary | Not Declared	16	4.284	4.907	3.661	1.271
Male	221	4.327	4.463	4.191	1.029

Note: N/A values are not included in the calculation of means. $N = 602$.

TABLE 10 Overall mean engagement scores (1 = Never, 7 = Always) for the United Kingdom and Ireland, sorted by increasing level of engagement.

			95% CI		
	N	Mean	Upper	Lower	*SD*
Ireland	97	3.817	4.066	3.568	1.251
United Kingdom	505	4.235	4.336	4.134	1.157

Note: N/A values are not included in the calculation of means. $N = 602$.

terms of social norms of open research, although well shy of the top of the scale, people generally felt that others in their wider research environment engage with and encourage the use of open research practices. In terms of the six COM-B dimensions, these responses aggregated to show that the lowest ratings were for social and physical opportunity, with psychological capability and automatic motivation in the middle range, and highest ratings related to physical capability and reflective motivation.

TABLE 11 Overall mean engagement scores (1 = Never, 7 = Always) for Russell Group and Non-Russell Group universities, sorted by increasing level of engagement.

			95% CI		
	N	**Mean**	**Upper**	**Lower**	***SD***
Non-Russell Group	435	4.081	4.192	3.970	1.184
Russell Group	167	4.393	4.567	4.219	1.148

Note: N/A values are not included in the calculation of means. $N = 602$. The Russell Group represents 24 of the United Kingdom's most research-intensive institutions.

TABLE 12 Overall mean engagement scores (1 = Never, 7 = Always) for institutional support (Yes, No, and Don't know responses), sorted by increasing level of engagement.

			95% CI		
	N	**Mean**	**Upper**	**Lower**	***SD***
Don't know	231	3.866	4.027	3.705	1.250
No	56	3.935	4.240	3.631	1.163
Yes	313	4.433	4.551	4.314	1.068

Note: N/A values are not included in the calculation of means. $N = 600$.

TABLE 13 Overall mean engagement scores (1 = Never, 7 = Always) for academic role of influence (Yes, No), sorted by increasing level of engagement.

			95% CI		
Academic role of influence	***N***	**Mean**	**Upper**	**Lower**	***SD***
No	263	4.039	4.197	3.880	1.310
Yes	339	4.267	4.380	4.154	1.063

Note: N/A values are not included in the calculation of means. $N = 602$.

Regression analyses

Effects of background and COM-B variables on mean research engagement

Table 18 shows the correlations between the ratings for all open research practices (see Supporting Information for full COM-B variable correlations). It is worth noting that there is a large range of correlations (from −0.042 to 0.879), suggesting that researchers are being selective about engaging in specific practices, rather than adopting an all-or-nothing approach to open research. Table 19 shows the results of the linear regression analysis for various background characteristics of academic rank, subdiscipline, research methodology, gender, institutional support, and country on mean engagement in research practices. Notably, there were no significant differences across academic ranks or across subdisciplines of psychology (all p's > .14). In terms of gender, female respondents showed significantly lower engagement than male respondents ($p = .004$), with no significant difference between undisclosed/non-binary and male respondents ($p = .32$). In terms of research methodology, neither qualitative nor quantitative researchers differed reliably from mixed methods researchers (p's > .56), although quantitative researchers do show significantly higher engagement than qualitative researchers overall ($p < .01$). There is a strong effect of institutional support (t-value = 5.986), with respondents who indicate awareness of support from their institutions showing significantly higher engagement in open research than those who are unaware of or felt that there was no institutional support ($p < .001$). Lastly, there was a weak effect

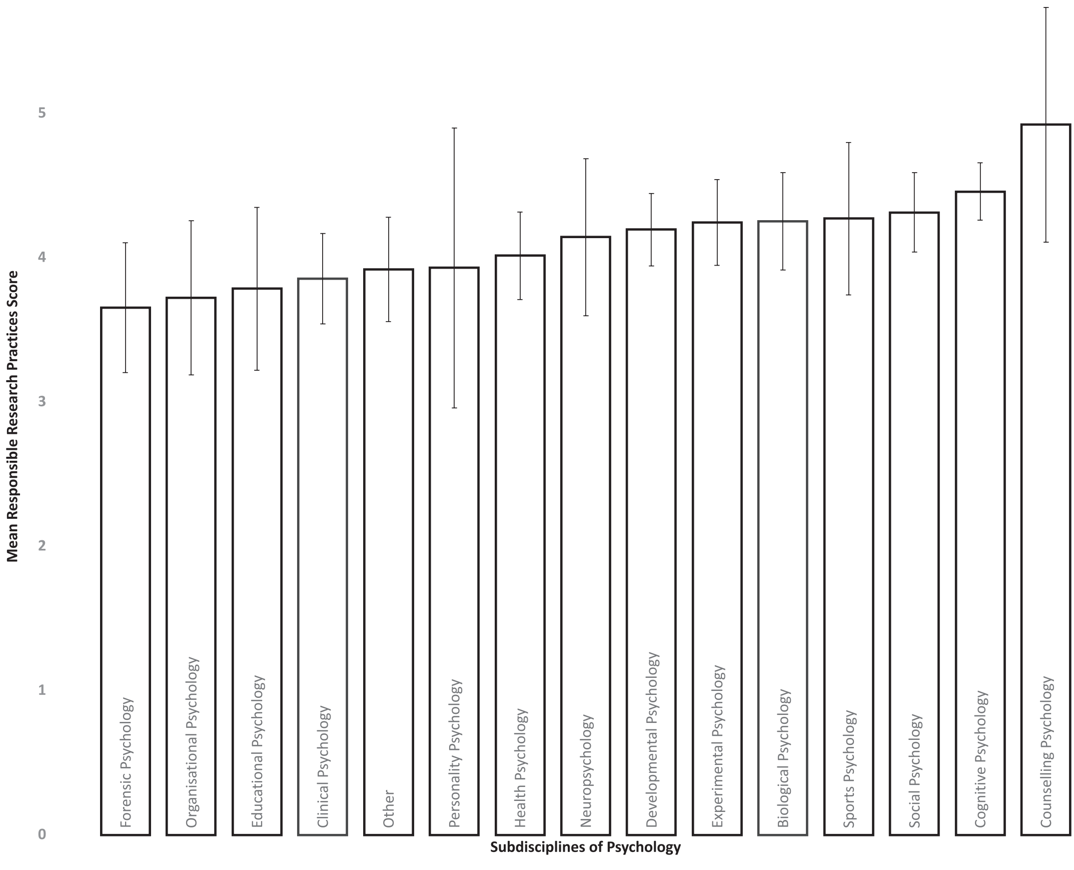

FIGURE 2 Mean engagement scores (1 = Never, 7 = Always) for each subdiscipline of psychology. Error bars represent 95% confidence intervals.

of country, with researchers in the United Kingdom showing significantly higher engagement in open research practices than those in Ireland ($p = .018$).

In line with our planned regressions, we also considered whether Russell Group membership and its interaction with academic rank had any effect on responsible research practices over and above the baseline background variables. Adding these variables had a weak, non-significant effect, F-Change(6, 572) = 1.832, R^2-change = .017, $p = .091$. There was a weak, non-significant effect of Russell group membership on its own ($p = .071$), and Russell Group membership did not interact with any levels of academic rank (all p's > .5).

We further examined the effect of institutional support on RRPs, over and above the baseline background variables. There was a strong effect of institutional support, F-Change(2, 574) = 20.912, R^2-change = .061, $p < .001$. There was no significant difference between respondents who answered 'Don't know' and 'No', but respondents who answered 'Yes' to the presence of institutional support had significantly higher mean research practice scores ($p < .001$).

Lastly, we examined the effect of holding academic roles of influence in a research capacity on responsible research practices (e.g., journal editor, member of board of learned society), over and above baseline background variables. There was a significant effect of positions of influence, F-Change(1, 577) = 22.341, R^2-change .033, $p < .001$, with those in positions of influence showing higher responsible research engagement than those who were not (see Table 13).

Next, we examined the relationship between COM-B factors and mean research engagement scores. In terms of bivariate correlations, automatic motivation, which is associated with developing the habit

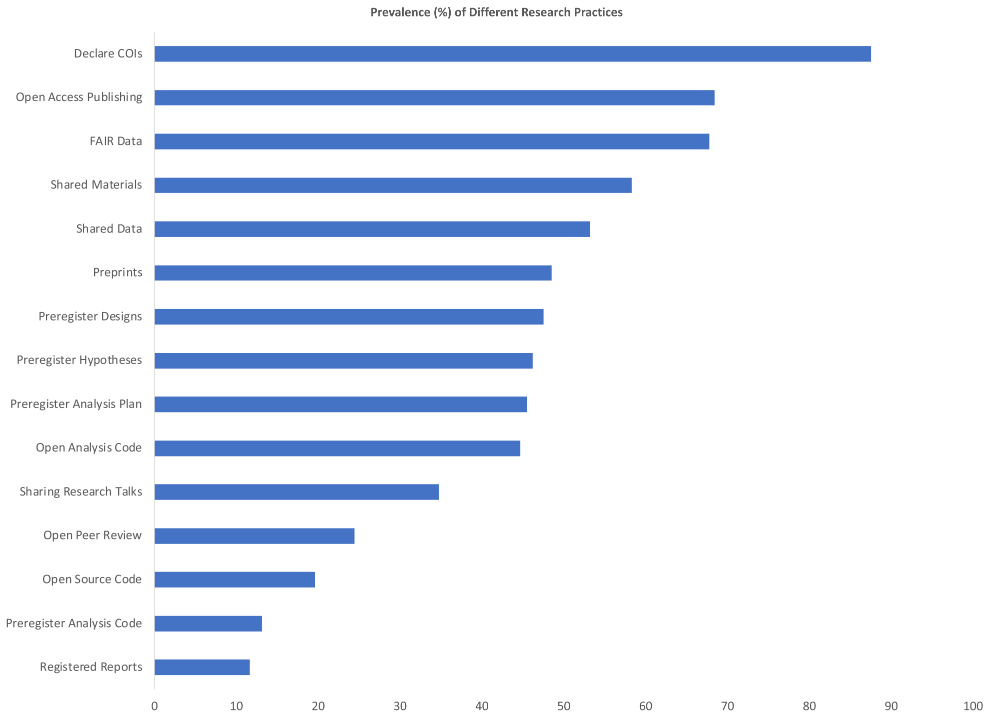

FIGURE 3 Prevalence (%) of different research practices, ordered by frequency.

of engaging with open research as an everyday part of the research process, has the strongest correlation of the six COM-B factors ($r = .685$). This compares with correlations for the other factors of physical capability ($r = .232$), psychological capability ($r = .545$), physical opportunity ($r = .480$), social opportunity ($r = .243$), and reflective motivation ($r = .485$). For each COM-B factor, higher ratings were associated with higher mean research practice scores.

Table 20 shows the regression results for COM-B factors on the overall mean responsible research practice scores. There was an overall effect of the combined COM-B variables when added to the baseline model [$R^2 = .543$, R^2 Change = .438, F-Change = 91.523, $df(6, 572)$, $p < .001$], with psychological capability, physical opportunity, social opportunity, and automatic motivation all significantly contributing to the model individually on overall engagement scores. Conversely, physical capability and reflective motivation had weak, non-significant effects on overall engagement. Complete reporting of all planned regressions from the Stage 1 submission can be found in the project's OSF Analysis page (https://osf.io/4ku8a/).

Effects of variables on study preregistration, registered reports, and participation in large-scale studies

Next, we examined the effects of COM-B variables on the individual practices of study preregistration, submitting Registered Reports, and taking part in large-scale or multi-site studies. There was an overall effect of COM-B variables on study preregistration ($df = 548$, $X^2 = 106.656$, $p < .001$, McFadden $R^2 = .147$), but only the factors of physical opportunity and automatic motivation were significant predictors when considered separately (Table 21). In separate analyses (see Supporting Information for full results), we found no effects of Russell Group membership or academic rank, but there were effects of institutional support and academic roles of influence, with those indicating institutional support or having research roles of influence being more likely to have preregistered a study.

TABLE 14 Prevalence of research practices, sorted by increasing prevalence, with the prevalence score, 95% confidence intervals and standard deviation (*SD*).

	Prevalence	95% CI Upper	95% CI Lower	*SD*
Registered reports	0.116	0.142	0.091	0.321
Preregister analysis code	0.131	0.158	0.104	0.338
Open-source code	0.196	0.228	0.164	0.397
Open peer review	0.244	0.279	0.21	0.43
Sharing research talks	0.347	0.385	0.309	0.476
Open analysis	0.447	0.487	0.407	0.498
Preregister analysis plans	0.455	0.495	0.415	0.498
Preregister hypotheses	0.462	0.502	0.422	0.499
Preregister designs	0.475	0.515	0.435	0.5
Preprints	0.485	0.525	0.445	0.5
Shared data	0.532	0.571	0.492	0.499
Shared materials	0.583	0.622	0.544	0.493
FAIR data	0.678	0.715	0.64	0.468
Open-access publishing	0.684	0.722	0.647	0.465
Declaring COIs	0.875	0.902	0.849	0.331

Note: Prevalence scores indicate the proportion of respondents in each category that responded with a rating of 5, 6, or 7 (where 7 is 'Always') indicating the frequency with which they engaged in each research practice.

For submitting Registered Report journal articles, there was also a significant effect of COM-B variables overall – $df = 541$, $X^2 = 56.396$, $p < .001$, McFadden $R^2 = .083$, with all dimensions except reflective motivation showing a significant effect when considered individually (Table 22). There was no significant effect of Russell Group membership or academic rank. There was a weak, non-significant effect of institutional support ($p = .058$), with those who indicated 'Yes' to institutional support more likely to have submitted a Registered Report article (36.1%) than those who indicated 'Don't know' (23.6%), but not reliably more likely than those who indicated 'No' (27.3%). There was also only a weak and non-significant effect of academic roles of influence ($p = .061$).

For participation in large-scale/multi-site studies, there was again an overall effect of COM-B variables – $df = 550$, $X^2 = 12.744$, $p = .047$, McFadden $R^2 = .017$, although the effect is noticeably weaker than their effect on preregistration and Registered Report submissions, and only automatic motivation emerges as a significant predictor when the factors are considered individually (Table 23). Although there was a significantly weak overall effect of Russell Group membership and its interaction with academic rank when added to the baseline model ($p = .038$), there was no significant effect of Russell Group membership on its own, nor any reliable interactions with the different levels of academic rank. There was no significant effect of institutional support, but there was a weak, significant effect of having an academic role of influence ($p = .017$).

Robustness analysis

To examine the robustness of the findings, we reran each analysis, excluding all responses that came via the social media version of the survey (i.e., including only those that were completed via direct emailing), giving $N = 512$. These additional analyses are included in the Supporting Information. While individual values move around a little (as would be expected), overall, we see very similar patterns for all analyses conducted. For the analysis of mean research practice scores, background variables showed similar effects, with weak or no effects of subdiscipline, academic rank, and research methodology.

TABLE 15 Mean engagement scores for each research practice (1 = Never, 7 = Always), sorted by increasing scores, 95% confidence intervals and standard deviation (*SD*).

					95% CI		
	N	N/A	N/A %	Mean	Upper	Lower	*SD*
Registered reports	556	46	7.6	2.165	2.303	2.028	1.660
Preregister analysis code	509	93	15.4	2.428	2.583	2.274	1.776
Open peer review	517	85	14.1	3.014	3.207	2.82	2.241
Sharing research talks	552	50	8.3	3.678	3.861	3.494	2.195
Preregister analysis plans	589	13	2.2	3.937	4.109	3.765	2.126
Open-source code	245	357	59.3	4.02	4.311	3.73	2.323
Open analysis	557	45	7.5	4.063	4.248	3.878	2.228
Preregister designs	590	12	2	4.078	4.245	3.911	2.072
Preregister hypotheses	581	21	3.5	4.081	4.248	3.914	2.057
Preprints	561	41	6.8	4.283	4.477	4.09	2.337
Shared data	577	25	4.2	4.477	4.643	4.31	2.037
Shared materials	579	23	3.8	4.63	4.785	4.475	1.903
FAIR data	574	28	4.7	5.171	5.312	5.029	1.730
Open-access publishing	565	37	6.1	5.189	5.314	5.065	1.506
Declaring COIs	551	51	8.5	6.695	6.779	6.611	1.004

Note: N/A responses are excluded from the calculation of means. *N* is the number of valid rating responses for each research practice, N/A is the number of N/A responses given, and as a % of the total responses (N/A%).

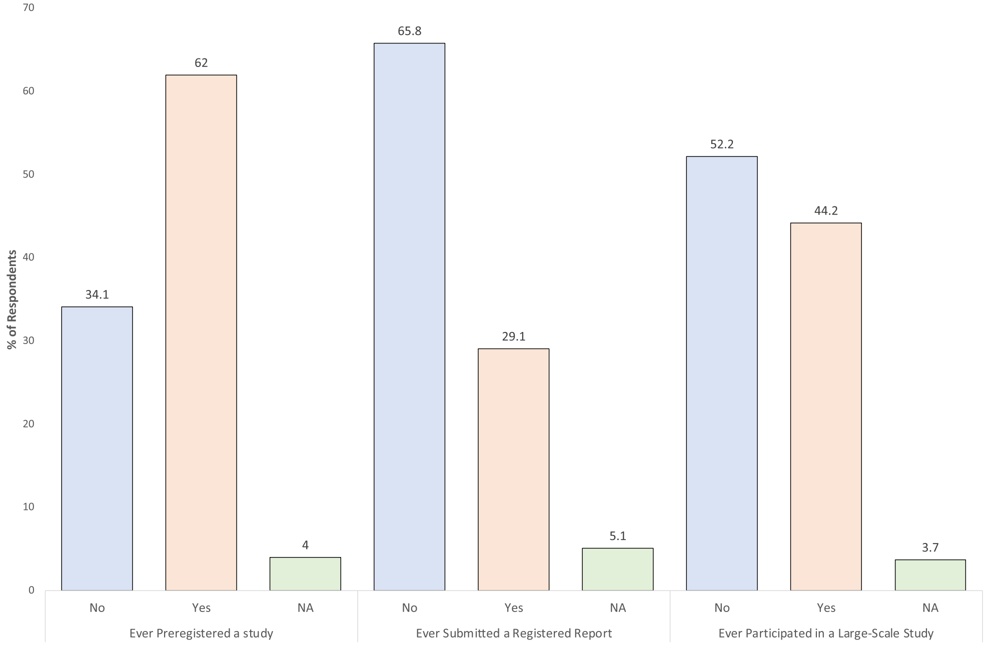

FIGURE 4 Percentage of respondents engaging in the specific research practices of study preregistration, submitting a registered report, or participating in a large-scale or multi-lab study.

There was a weaker effect of gender, but when examined separately, female respondents again showed significantly lower mean responsible research practice scores than male respondents. There were again significant effects of institutional support and Country. We observed a slightly stronger effect of Russell

TABLE 16 Mean scores (1 = Strongly Disagree, 7 = Strongly Agree) for each of the COM-B questions, and the corresponding COM-B dimension to which they relate.

Statement	COM-B Dimension	*N*	N/A	Mean	95% CI Upper	95% CI Lower	*SD*
I am physically capable of engaging in open research practices (e.g., I have sufficient physical stamina, I have sufficient physical skills)	Physical Capability	585	17	6.159	6.262	6.056	1.277
I am equipped with the skills necessary to engage with open research practices	Psychological Capability	600	2	5.47	5.586	5.354	1.45
I have enough information and training on open research practices	Psychological Capability	600	2	4.893	5.03	4.756	1.713
I have access to the appropriate research infrastructure to engage in open research practices (e.g., access to appropriate repositories, computing resources etc.)	Physical Opportunity	601	1	5.403	5.535	5.271	1.652
I have enough time to implement open research practices in my work	Physical Opportunity	600	2	3.993	4.137	3.85	1.795
I have sufficient financial support to engage in open research (e.g., to cover costs of video recordings, transcription/translation, data storage etc.)	Physical Opportunity	591	11	3.415	3.563	3.266	1.845
Others in my wider research environment engage with and encourage the use of open research practices	Social Opportunity	599	3	5.018	5.139	4.898	1.509
There are adequate incentives from funders, institutions or other regulators to engage in open research	Social Opportunity	582	20	3.775	3.92	3.63	1.789
There is sufficient recognition of open research in promotion and recruitment criteria	Social Opportunity	578	24	3.351	3.493	3.209	1.741
I am sufficiently motivated to engage with open research practices	Reflective Motivation	600	2	5.212	5.343	5.08	1.643
I believe open research practices to be a positive thing	Reflective Motivation	597	5	6.265	6.359	6.17	1.179
I consciously plan on working more with open research practices in the future	Reflective Motivation	594	8	5.992	6.099	5.884	1.34
I have developed the habit of engaging in open research practices as an everyday part of my research process	Automatic Motivation	596	6	4.782	4.936	4.627	1.924
When I think about my research, I automatically think about the open research elements as well	Automatic Motivation	601	1	5.015	5.167	4.863	1.901

Note: Table shows the number of responses (*N*), number of N/A responses, mean rating, 95% confidence intervals, and standard deviation (*SD*).

TABLE 17 Mean scores (1 = Strongly Disagree, 7 = Strongly Agree) for the six COM-B dimensions.

		95% CI		
	Mean	Upper	Lower	*SD*
Physical capability	6.098	6.203	5.993	1.309
Psychological capability	5.178	5.296	5.059	1.483
Physical opportunity	4.273	4.386	4.16	1.414
Social opportunity	4.058	4.159	3.956	1.267
Reflective motivation	5.806	5.902	5.71	1.2
Automatic motivation	4.894	5.039	4.748	1.821

Group membership on overall engagement, but as before there were no significant interactions with any level of academic rank.

COM-B variables collectively were still significant predictors of mean engagement in research practice scores, with an identical pattern of psychological capability, physical opportunity, social opportunity, and automatic motivation emerging individually as significant predictors, and physical capability and reflective motivation as non-significant predictors. In a deviation from the main analysis, there was an effect of Russell Group membership, but not its interactions with academic rank. As before, there continued to be effects of institutional support, and of having an academic role of influence.

COM-B variables were also collectively significant predictors of having preregistered at least one study as a lead researcher, with the same pattern of physical opportunity and automatic motivation again emerging as significant predictors. In the additional analyses, Russell Group membership and its interaction with academic rank again had no significant effect. Institutional support continued to have a strong effect, and having an academic role of influence also had an effect, as before.

For the question of whether people had submitted at least one Registered Report article, there was again an overall effect of the combined COM-B variables. However, there were weaker effects of the COM-B variables individually, with physical capability, physical opportunity and social opportunity now non-significant. As before, there was no effect of Russell Group membership, a similarly weak effect of institutional support, and the effect of having an academic role of influence was again non-significant.

For the question of whether people had participated in at least one large-scale or multi-lab study, we also observed very similar patterns for the COM-B variables, with a significant overall effect for the combined COM-B variables, and a significant effect of automatic motivation. In a deviation from the main analysis, physical capability also emerges with a weak significant effect ($p = .044$). Where there was a weak effect of Russell Group membership in the main analysis, that was no longer evident. As before, there was no effect of institutional support, and the weak effect of academic role of influence was no longer present.

While there are some deviations from the primary analyses to ensure high data quality, the overall patterns remain very similar. Indeed, we would not necessarily expect completely identical results, since participants' characteristics are likely to vary from those who completed the survey via a personal email to those who completed it via a social media link. Nonetheless, it is reassuring that the general patterns are similar.

DISCUSSION

In a survey of 602 psychology researchers in the United Kingdom and Ireland, we found broad, yet variable, engagement with fifteen open research practices. Prevalence estimates showed that a majority of respondents were engaged in five practices (e.g., declaring COIs, open-access publishing, FAIR data, shared materials, shared data), while between 40% and 50% were engaged in another five (e.g., preprints, preregistering designs, preregistering hypotheses, preregistering analysis plans, open analysis code), and a minority between 11.6% and 34.7% engaged in the final five practices (e.g., sharing research talks,

TABLE 18 Pearson correlations for the ratings of all 15 responsible research practices.

Research practice	Declaring COIs	Shared materials	FAIR data	Shared data	Open analysis	Open source code	Preregister hypotheses	Preregister designs	Preregister analysis plans	Preregister analysis code	Registered reports	Preprints	Open access publishing	Open peer review	Sharing research talks
Declaring COIs	—														
Shared materials	.168	—													
FAIR data	.222	.548	—												
Shared data	.154	.651	.579	—											
Open analysis	.123	.595	.487	.654	—										
Open-source code	.018	.328	.261	.356	.483	—									
Preregister hypotheses	.067	.345	.342	.385	.346	.117	—								
Preregister designs	.036	.316	.344	.362	.348	.104	.864	—							
Preregister analysis plans	.018	.353	.34	.402	.374	.129	.857	.879	—						
Preregister analysis code	−.042	.257	.253	.294	.406	.337	.4	.429	.463	—					
Registered reports	−.048	.148	.153	.209	.207	.204	.276	.308	.311	.416	—				
Preprints	.187	.256	.292	.332	.264	.157	.226	.198	.211	.242	.185	—			
Open-access publishing	.215	.123	.152	.086	.063	.037	.05	.043	.048	.061	.129	.223	—		
Open peer review	.082	.061	.113	.094	.009	−.003	.027	.027	.032	.14	.199	.15	.167	—	
Sharing research talks	.107	.147	.172	.171	.139	.121	.112	.099	.098	.197	.217	.198	.176	.334	—

Note: $N = 602$; NA values have been replaced by a score of 1 (never been done).

TABLE 19 Effect of background variables: academic rank, gender, sub-discipline, research method, institutional support, and country, on the overall mean responsible research practice score.

Characteristic	Sub-category	B	t	p-Value	95% CI Lower	95% CI Upper
Academic rank (reference category is Assistant Professor/Lecturer)	Prof/Associate Prof	−0.09	−0.813	.417	−0.307	0.127
	Other	0.366	0.965	.335	−0.379	1.112
	PhD student	−0.191	−1.476	.141	−0.444	0.063
	Postdoctoral researcher	0.242	1.398	.163	−0.098	0.581
	Research fellow	0.023	0.1	.921	−0.429	0.475
Gender (reference category is male)	Female	−0.284	**−2.926**	**.004**	−0.475	−0.093
	Undisclosed/non-binary	−0.267	−0.996	.319	−0.793	0.259
Sub-discipline (reference category is biological psychology)	Clinical	−0.184	−0.696	.486	−0.704	0.336
	Counselling	0.259	1.255	.21	−0.146	0.665
	Developmental	0.756	1.344	.179	−0.348	1.86
	Educational	−0.111	−0.486	.627	−0.559	0.337
	Experimental	−0.135	−0.397	.692	−0.802	0.533
	Forensic	−0.073	−0.305	.761	−0.547	0.4
	Health	−0.344	−1.072	.284	−0.976	0.287
	Neuropsychology	−0.173	−0.749	.454	−0.628	0.281
	Organizational	−0.037	−0.129	.897	−0.603	0.529
	Other	−0.229	−0.806	.42	−0.788	0.329
	Personality	−0.329	−1.37	.171	−0.8	0.143
	Social	−0.137	−0.317	.751	−0.981	0.708
	Sports	0.045	0.199	.842	−0.403	0.494
Research method (reference category is mixed methods)	Qualitative	−0.108	−0.582	.561	−0.471	0.256
	Quantitative	0.027	0.236	.813	−0.201	0.256
Institutional support (reference category is do not know)	No support	0.194	1.22	.223	−0.118	0.507
	Yes support	0.575	**5.986**	**<.001**	0.386	0.763
Country (reference category is Ireland)	United Kingdom	0.288	**2.38**	**.018**	0.05	0.526

Note: The regression contains all of the above background variables. For each characteristic and sub-category, the table shows unstandardized coefficients, *t*-value, *p*-value, and the 95% confidence intervals for the coefficient. Significant differences from the reference category (at $p < .05$) are highlighted in bold.

open peer review, open source code, preregistering analytical code, submitting Registered Reports). We observed no strong differences according to the subdiscipline of psychology or academic rank of the respondents, and mixed effects related to Russell Group membership and academic roles of influence. However, we did see significant differences according to gender (with male respondents indicating greater engagement in open research) and preferred research methodology (with quantitative researchers showing greater engagement).

This observed gender difference is consistent with the findings of Gopalakrishna et al. (2022), although they offer no suggestions as to why this may be the case. One possibility is that female researchers are more represented in qualitative research than male researchers, and given qualitative researchers can face unique challenges when engaging in open research practices (Pownall et al., 2023), this may lead to lower overall engagement. However, an exploratory regression analysis (included in the project's OSF repository) suggests this possibility is not well supported by our current data, with no reliable interaction observed between gender and research methodology. However, we do observe some gender

TABLE 20 Regression results of COM-B factors of physical capability, psychological capability, physical opportunity, social opportunity, reflective motivation, and automatic motivation on the overall mean responsible research practice scores.

				95% CI	
COM-B factor	***B***	***t***	***p*-Value**	**Lower**	**Upper**
Physical capability	−0.048	−1.687	.092	−0.104	0.008
Psychological capability	0.127	**3.938**	**<.001**	0.064	0.191
Physical opportunity	0.108	**3.262**	**.001**	0.043	0.173
Social opportunity	−0.071	**−2.371**	**.018**	−0.131	−0.012
Reflective motivation	0.053	1.462	.144	−0.018	0.125
Automatic motivation	0.307	**11.657**	**<.001**	0.255	0.358

Note: Table shows unstandardized coefficients (B), t-values, p-values, and the 95% confidence intervals around the coefficient. $N = 602$. Significant effects at $p < .05$ are highlighted in bold.

TABLE 21 Results for COM-B factors of physical capability, psychological capability, physical opportunity, social opportunity, reflective motivation, and automatic motivation on whether respondents have ever preregistered a study as a lead researcher (excluding N/A responses to this question).

				95% CI	
COM-B factor	***B***	**Wald**	***p*-Value**	**Lower**	**Upper**
Physical capability	−0.059	0.476	.49	−0.228	0.109
Psychological capability	0.144	2.153	.142	−0.048	0.337
Physical opportunity	0.205	**3.872**	**.049**	0.001	0.41
Social opportunity	−0.14	2.049	.152	−0.332	0.052
Reflective motivation	−0.113	1.017	.313	−0.332	0.106
Automatic motivation	0.501	**35.005**	**<.001**	0.335	0.667

Note: $N = 578$. Table includes the unstandardized coefficient, Wald value, p-value, and 95% confidence intervals of the unstandardized coefficient. Significant effects at $p < .05$ are highlighted in bold.

TABLE 22 Results for the COM-B factors of physical capability, psychological capability, physical opportunity, social opportunity, reflective motivation, and automatic motivation on whether respondents have ever submitted a Registered Report journal article (excluding N/A responses to this question) $N = 571$.

				95% CI	
COM-B factor	***B***	**Wald**	***p*-Value**	**Lower**	**Upper**
Physical Capability	−0.237	**6.161**	**.013**	−0.424	−0.05
Psychological Capability	0.339	**9.373**	**.002**	0.122	0.556
Physical Opportunity	0.231	**4.605**	**.032**	0.02	0.441
Social Opportunity	−0.202	**4.479**	**.034**	−0.388	−0.015
Reflective Motivation	−0.074	0.367	.545	−0.314	0.166
Automatic Motivation	0.239	**6.914**	**.009**	0.061	0.417

Note: Table includes the unstandardized coefficient, Wald value, p-value, and 95% confidence intervals of the unstandardized coefficient. Significant effects at $p < .05$ are highlighted in bold.

differences along COM-B dimensions, which indicate that female participants gave lower ratings than male participants on physical capability, psychological capability, physical opportunity, and automatic motivation. Looking at specific questions within these dimensions, we see that males are more likely to indicate they have the skills necessary and have sufficient training to engage in open research. By contrast, female respondents indicated that they have less time and financial support for open research,

TABLE 23 Results for the COM-B factors of physical capability, psychological capability, physical opportunity, social opportunity, reflective motivation, and automatic motivation on whether respondents have ever taken part in a large-scale, or multi-lab study (excluding N/A responses to this question).

				95% CI	
COM-B factor	***B***	**Wald**	***p*-Value**	**Lower**	**Upper**
Physical capability	0.037	0.213	.645	−0.121	0.195
Psychological capability	0.107	1.368	.242	−0.072	0.285
Physical opportunity	−0.11	1.377	.241	−0.293	0.073
Social opportunity	0.036	0.182	.67	−0.131	0.204
Reflective motivation	−0.028	0.074	.785	−0.227	0.172
Automatic motivation	0.154	**4.294**	**.038**	0.008	0.299

Note: $N = 580$. Table includes the unstandardized coefficient, Wald value, *p*-value, and 95% confidence intervals of the unstandardized coefficient. Significant effects at $p < .05$ are highlighted in bold.

despite being just as likely as male respondents to indicate engaging more with open research in the future and believing that it is a positive thing. Thus, while there is certainly a need for greater support generally to encourage engagement with open research, female researchers, who for example often carry a greater burden of service roles (Guarino & Borden, 2017), may need additional support to achieve parity with male researchers.

For other variables, although mean values showed that respondents from Russell Group universities were more engaged in open research, the effect was weak, and not significant when background variables weree controlled for in key regression analyses. Stronger effects were observed depending on whether participants' institutions supported open research, with respondents from those institutions showing higher engagement scores, even after controlling background variables, and emerging across several different analyses. We also saw that respondents who held academic roles of influence had higher engagement in RRPs, as did respondents based in the United Kingdom, relative to those based in Ireland. Thus, while there is much to be hopeful about, psychology has a long way to go before open research practices throughout the research cycle are fully normalized.

Collectively, all six COM-B dimensions were related to engagement in RRPs, with their combined influence significant in almost all analyses conducted. Individually, automatic motivation appeared to be the strongest and most consistent dimension, emerging as a significant predictor in almost all analyses, while other COM-B factors were significant in some analyses, but not others. Automatic motivation relates to the extent to which researchers have integrated RRPs into their workflows to the point where they automatically think of them when they think of their own research.

It is important to note that the exact mechanism for the relationship between automatic motivation and open research practices is currently unknown. It is possible that open research practices becoming habitual could reduce the cognitive burden on researchers, as they would no longer need to deliberate over whether to engage in these practices each time they encounter them in their workflow. This could enable these researchers to engage in RRPs without relying on conscious decision-making processes. However, we still do not know why some researchers have automatic motivation to engage in open research practices and others do not. It is possible that engaging in some open research practices and seeing their benefit leads to adoption into the researcher's workflow. It is also possible that researchers who intrinsically associate open research with their scientific identity are more likely to integrate these practices more automatically into their research workflow. More research is needed to better understand the relationship between automatic motivation and uptake of RRPs.

While automatic motivation was the most robust dimension of the COM-B variables, the dimensions of psychological capability (i.e., how well prepared people are for open research practices), physical opportunity (i.e., whether people have sufficient time, money, and access to adequate infrastructure), and social opportunity (i.e., whether others around you use open research, and whether there are sufficient incentives and recognition) also appeared as significant predictors in multiple analyses, highlighting the fact that people's engagement in open research is multi-faceted, with different factors being perceived as more or less important, depending on the nature of the specific research practice, and perhaps other contextual factors.

These patterns align with those observed by Norris et al. (2022) who also found that adequate funding (physical opportunity), incentives (social opportunity), training and knowledge of open practices (psychological capability), and recognition of open research (social opportunity) were all perceived by researchers as supportive processes that could encourage them to adopt more open research practices in their work. Norris et al. also found that reflective motivation was of generally low importance for researchers, which chimes with our findings that it was not a consistently reliable predictor of engagement with RRPs. Finally, while we found that automatic motivation was the most consistently important of the COM-B dimensions, Norris and colleagues did not include questions related to automatic motivation or physical capability, so we cannot make direct comparisons in this regard, but suggest that it should be a dimension considered in future surveys of open research practices.

In the survey of Dutch researchers, although Gopalakrishna et al. (2022) did not explicitly implement questions that focussed on COM-B dimensions, a number of their findings clearly align with these factors. For example, reflecting social opportunity, subscribing to scientific norms (which were rated similarity across all disciplines and all academic ranks) and greater mentoring support (psychological capability) were both found to be associated with greater engagement with RRPs. Therefore, across studies, important relationships between measured COM-B dimensions and extent of engagement in RRPs are borne out, which we can take into account when we think about open research initiatives and how best to foster greater engagement.

Given the relevance of multiple intrinsic and extrinsic factors on levels of engagement, open research initiatives would be wise to take a holistic approach that encompasses not only personal and technical aspects (physical capability, physical opportunity) but also cognitive and motivational dimensions (psychological capability, automatic motivation), as well as the broader social context (social opportunity) in which researchers operate.

To improve psychological capability, open research initiatives need to provide researchers with the necessary technical skills and tools required for data sharing, collaboration, transparency, and so on. It is not enough to simply increase awareness; researchers need to know how to practically implement these practices in their own research domains. Physical and social opportunity are also clearly important. It may be self-evident, but it needs to be acknowledged that engaging with certain open research practices, such as sharing materials or sharing data in a FAIR format, takes additional time and resources. Institutions and funders need to bear this in mind when they are, for example, evaluating performance or outputs for promotion, or assessing a project's value for money. Researchers who are sufficiently engaged in open research will necessarily have less time to devote to other activities, but such practices are likely to result in higher-quality research.

Increasing social opportunity through networking events, conferences, and collaborative platforms where researchers can engage with others in open research practices can help normalize open research behaviours, with social norms being powerful mediators of actual behaviours (Cialdini & Jacobson, 2021). Again, research funders and institutions can do their part, not only by recognizing the importance of open research but also rewarding and adequately supporting it through their awards and incentive structures. Researchers need to see the value in open science for their work and careers. Since our findings show robust effects of institutional support on the uptake of RRPs, it is critical that universities demonstrate to researchers that they are providing visible and tangible support for open research practices, for example, by supporting local open research networks or appointing institutional leads for open research (UK Reproducibility Network Steering Committee, 2021).

Employers can explicitly provide time for researchers to engage in open research training, and embed open research into their hiring and promotion criteria, so that researchers are tangibly rewarded for their efforts, rather than in the current culture, where researchers are ultimately being punished for example, by spending extra time ensuring their data is FAIR compliant, instead of ignoring such practices and spending that time publishing additional journal articles, which might explicitly count towards promotion or hiring criteria. Greater provision of opportunities, acknowledgement, recognition, and career benefits associated with open research can serve as powerful motivators for increasing engagement.

Such actions will then feed into researchers' reflective motivation (i.e., their belief that open research is good, and their intention to engage more in open research in the future), by making clear the benefits of open research for them as individuals. For enhancing the view that open research is good for science more generally, showcasing successful open research projects and demonstrating how open practices can lead to higher-quality research would be another option. For example, informing people that Registered Report articles are perceived as higher-quality relative to standard (non-registered) journal articles without any perceived differences in novelty and creativity (Soderberg et al., 2021) may make them more likely to consider this route to publication in the future. Thus, for any given COM-B dimension, there are many possible supports or interventions that could be implemented that could ultimately lead to increased uptake of open research practices.

While the specific focus of the current work is on positive aspects of open research, the COM-B measure provided additional insight into why researchers might *not* engage with responsible research practices. Institutions and funders therefore also need to be aware of the flipside and consider what factors might lead researchers to engage in more questionable research practices. When institutions set a goal of moving up university rankings, where 'number of publications' is a component of how rankings are calculated, they may inadvertently encourage researchers to engage in more questionable practices, while simultaneously discouraging uptake of more responsible ones. Reducing this pressure to publish and to find statistically significant results while increasing awareness of open practices have all been associated with reducing researcher motivations for engaging with QRPs (Janke et al., 2019; Ludwig et al., 2023).

Deviations and limitations

As covered in the Method section, we detailed why we felt the need to deviate from our original data pre-processing plan, due to the high rate of bot/suspicious responses. While the level of suspicious responses appears very high, it is comparable with estimates provided in a recent paper by Goodrich et al. (2023), who, in two different online surveys of the U.S. beekeeping industry found rates of fraudulent responses of 96% and 72%. It is worth noting that the surveys discussed by Goodrich et al. did not use enhanced fraud protection options in Qualtrics, whereas we had enabled these options for both versions of the current survey. Nevertheless, selecting these options seemed to have a negligible impact on resisting the bot onslaught. Thus, while we can be reasonably confident that we excised the vast majority of suspicious responders, it is a cautionary tale for others conducting online studies that recruit via social media. Although it may deter some potential respondents, researchers should incorporate multiple checks to assure high-quality data are collected (e.g., CAPTCHA or other bot-detection techniques, attention checks etc. See Goodrich et al., pp. 775–779 for detailed recommendations).

In terms of other limitations, we acknowledge that any survey tool brings with it some limitations and trade-offs. This survey was implemented to allow responses to be anonymous, and we must acknowledge that such a choice may impact people's responses. On the one hand, anonymous responses prevent us from requesting further useful information (e.g., such as asking people to provide evidence of their engagement in various research practices). On the other hand, requiring people to provide their identities may lead to more socially desirable responding, for example by rating their level of engagement in open research practices as being much higher, since they know their responses are tied to their identity.

The impact of anonymous versus non-anonymous responding is an open empirical question – and an interesting meta-scientific one – but not one we can do justice to in the current study. However, evidence suggests that anonymous surveys tend to result in a lower level of social desirability than non-anonymous surveys (see Dodou & de Winter, 2014 for a meta-analysis of such effects). Furthermore, many studies also show that those who believe their behaviour is being monitored, or lacking privacy, moderate their behaviour in response to this belief (Bateson et al., 2006), and then conform to perceived norms rather than providing responses that reflect their own beliefs and behaviours (Kaminski & Witnov, 2014). On balance, we felt that the risk of socially desirable responding was probably greater for non-anonymous responding, and so retaining anonymity for all participants was the preferred option for the current study.

Additionally, survey respondents self-select whether they participated or not. Although this is possibly the largest survey of open research practices in psychology in the United Kingdom and Ireland so far, we are nonetheless missing out on the responses of thousands of other researchers. It may be that respondents in the current survey are already more interested in open research than these other researchers in psychology, and so our findings may overestimate the prevalence and level of engagement with open research. Alternatively, there may be no differences in views on open research, with non-respondents not participating for various other reasons. Researchers are frequently asked to give views in one survey or another, so survey fatigue is a genuine issue facing researchers in this domain, and it is often challenging to achieve sufficiently large and representative samples in this kind of research.

A knock-on effect of the smaller than hoped sample size, and data loss in the social media version of the survey, is that we have very small numbers for some subdisciplines of psychology, which leads to large confidence intervals around estimates. It may take a much more targeted approach (e.g., via discipline-specific conferences or learned societies) to get sufficiently informative samples for these areas of research. Online surveys can also be usefully complemented by other approaches, such as evaluations of journal interventions (e.g., the introduction of open science badges – Hardwicke et al., 2021) or literature surveys to estimate the prevalence of specific research practices in particular journals or subdomains (Towse et al., 2021).

CONCLUSIONS AND FUTURE DIRECTIONS

This study provides a snapshot of engagement in responsible research practices in psychologists from the United Kingdom and Ireland and considers some explanatory factors based on the COM-B model of behaviour change for researcher engagement in open research. This provides several avenues for further research including additional secondary analyses of the (open) data collected (e.g., cross-country comparisons), re-use of the open materials and survey questions to conduct follow-up studies to track engagement over time or across different countries, or even to develop and test interventions based on the emergence of individual predictors of enhanced engagement. We hope that this work will contribute to developing a richer picture both in terms of level of uptake and people's motivations for engaging in responsible research practices.

AUTHOR CONTRIBUTIONS

Priya Silverstein: Conceptualization; methodology; writing – original draft; writing – review and editing. **Charlotte R. Pennington:** Conceptualization; investigation; methodology; writing – original draft; writing – review and editing. **Peter Branney:** Conceptualization; investigation; methodology; writing – original draft; writing – review and editing. **Daryl B. O'Connor:** Conceptualization; investigation; methodology; writing – original draft; writing – review and editing. **Emma Lawlor:** Methodology; resources; writing – original draft. **Emer O'Brien:** Resources; validation; writing – review and editing. **Dermot Lynott:** Conceptualization; data curation; investigation; methodology; project administration; resources; visualization; writing – original draft; writing – review and editing.

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CONFLICT OF INTEREST STATEMENT

We have no known conflict of interest to disclose.

OPEN RESEARCH BADGES

This article has earned Open Data, Open Materials and Preregistered Research Design badges. Data, materials and the preregistered design and analysis plan are available at https://osf.io/xjby2/; DOI: 10.17605/OSF.IO/XJBY2.

DATA AVAILABILITY STATEMENT

Analyses were conducted in JASP (Version 0.18, Wagenmakers et al., 2018), and all scripts and output files are publicly available on the project's OSF page (https://osf.io/xjby2/). Raw, anonymized data are available, with specific institutional information withheld to protect the identity of respondents and institutions.

ORCID

Priya Silverstein https://orcid.org/0000-0003-0095-339X
Charlotte R. Pennington https://orcid.org/0000-0002-5259-642X
Peter Branney https://orcid.org/0000-0002-2084-461X
Daryl B. O'Connor https://orcid.org/0000-0003-4117-4093
Emma Lawlor https://orcid.org/0000-0002-7923-2714
Emer O'Brien https://orcid.org/0009-0006-9369-3046
Dermot Lynott https://orcid.org/0000-0001-7338-0567

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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APPENDIX A

Survey Structure and Questions

Note the headings for different subsections are not visible to survey respondents.

Part 1

Start, Participant Information & Informed Consent
(continue or decline if no consent)

Part 2

Demographics and research

Based in a HEI in the United Kingdom or Ireland (exit if answer = other)

Engage in research activities (8 h per week minimum, including supervision – exit if not >8 h per week)

Psychology subdiscipline (11 options)

Primary methodology used – quantitative, qualitative, mixed methods

academic rank

PhD student or junior researcher

Postdoctoral researcher,

Research Fellow/Senior Research Associate

Assistant Professor/Lecturer

Associate Professor, Senior Lecturer, Reader or Professor

None of the above

Gender (open question)

Part 3

Research Practice Questions

Part 4

Explanatory Factor Questions – Capability, Opportunity, Motivation

Additional Questions, e.g., institutional support

Any other comments

Part 5

Debrief, Enter Draw and End.

RESPONSIBLE RESEARCH PRACTICES SURVEY QUESTIONS

Please rate on the 1–7 scale (or select N/A if not applicable) each of the following questions.

A rating of '1' indicates 'Never', while a rating of '7' indicates 'Always'. For example, if you usually, but not always, do Practice A, you might select 5 or 6 on the scale, while if you have Never done Practice A, you would select 1.

Where reference is made to a public repository, we mean anywhere that a member of the public could access that information. This could include personal web pages, university repositories, as well as large-scale repositories like the Open Science Framework, Github, Zenodo, preprint servers (PsyArxiv, BioArxiv etc.) and many more.

CONFLICTS OF INTEREST

1. I always disclose who funded my studies and all my relevant financial and non-financial interests in my publications

MATERIALS AND DATA

Shared materials

2. I deposit my study materials and stimuli on a publicly accessible repository

Shared data

3. I contribute, where appropriate, to making my research data findable, accessible, interoperable and reusable in accordance with the FAIR principle
4. I deposit the raw anonymized data, and processed data (used for reported analyses) on a publicly accessible repository OR, where data anonymization is not possible, I deposit my identifiable raw and processed data in a controlled archive that provides access to future researchers.

Shared analysis and code

5. I deposit analysis scripts, analysis code, or statistical output files on a publicly accessible repository
6. I deposit source code for any computational research (e.g., neural networks, machine learning, cognitive architectures etc.) on a publicly accessible repository

PREREGISTRATION AND REGISTERED REPORTS

Preregistration of studies prior to collecting data

7. I preregister my study hypotheses, and make them available on a publicly accessible repository (e.g., AsPredicted, OSF etc.,)
8. I preregister study designs/protocols, and make them accessible on a publicly accessible repository
9. I preregister analysis plans, and make them available on a publicly accessible repository
10. I preregister analysis code or scripts (e.g., R code, syntax files), and make them available on a publicly accessible repository

Registered reports

11. I submit manuscripts for publication as Registered Reports (i.e., where the manuscript is reviewed, and may receive in-principle acceptance, prior to data collection and analysis)

DISSEMINATION AND REVIEW

Preprints

12. I make my academic manuscripts freely available prior to publication, for example via a preprint repository (e.g., PsyArXiv, BioArxiv, OSF Preprints etc.), personal web page or other fully open online repository
13. I publish my work in open-access journals
14. I sign my reviews when peer-reviewing manuscripts
15. I share slides from my research talks on a publicly available repository, or agree to have a research talk I've given made publicly available (e.g., via YouTube or other online platform)

FIRST CONTACT WITH OPEN RESEARCH

16. Could you estimate the year that you first engaged with any of the open research practices described previously? Enter the year (e.g., 2017), or n/a.
17. I have preregistered at least one study, where I have been the principle or a lead researcher on the project (Yes/No)
18. I have submitted at least one registered report format article (Yes/No)
19. I have taken part in a large-scale or multi-site study (involving a replication or original research)

CAPABILITY, OPPORTUNITY, MOTIVATION, AND GENERAL ATTITUDE QUESTIONS (WHERE 1 INDICATES STRONGLY DISAGREE, AND 7 INDICATES STRONGLY AGREE)

Physical Capability

20. I am physically capable of engaging in open research practices (e.g., I have sufficient physical stamina, I have sufficient physical skills)

Psychological Capability

21. I am equipped with the skills necessary to engage with open research practices
22. I have enough information and training on open research practices

Physical Opportunity

23. I have access to the appropriate research infrastructure to engage in open research practices (e.g., access to appropriate repositories, computing resources etc.)
24. I have enough time to implement open research practices in my work
25. I have sufficient financial support to engage in open research (e.g., to cover costs of video recordings, transcription/translation, data storage etc.)

Social Opportunity

26. Others in my wider research environment engage with and encourage the use of open research practices
27. There are adequate incentives from funders, institutions or other regulators to engage in open research
28. There is sufficient recognition of open research in promotion and recruitment criteria

Reflective Motivation

29. I am sufficiently motivated to engage with open research practices
30. I believe open research practices to be a positive thing
31. I consciously plan on working more with open research practices in the future

Automatic Motivation

32. I have developed the habit of engaging in open research practices as an everyday part of my research process
33. When I think about my research, I automatically think about the open research elements as well

Institutional Support (Yes/No/Don't know)

34. Does your Department or University have an open research working group, or an open research institutional lead (e.g., affiliated with the UK Reproducibility Network or similar)?

Influential Roles (tick box)

35. We are interested in exploring the link between positions of influence and research practices. Have you held any of the following research-related roles in the last 5 years? Please select all that apply.
    a. Journal Editor/Associate Editor
    b. Grant Assessment Panel Member of a funding body
    c. Member of the board of a learned society
    d. Member of a government advisory panel
    e. Senior management of university in a research capacity
    f. Member of open research working group or wider network
    g. Other position of influence relating to research (free text)

Open Response Question

Do you have any additional comments to make regarding open research generally, or regarding benefits/challenges to engaging with open research practices? (open text box).

A draft Qualtrics survey is available here: https://maynoothpsychology.qualtrics.com/jfe/form/SV_5p9kSzMrtuG3Ybk.

APPENDIX B

Statistical analysis plan

First, to summarize the overall analytical approach, the analyses will start with basic descriptions of the data, followed by examination of relationships between variables, and more complex analyses concerning the relationships between engagement in open research practices and the explanatory factors that potentially impinge on engagement (e.g., capability, opportunity, motivation). We provide a detailed analysis plan below. Note that there is always the possibility that further analyses may be conducted in the future, or for this data to be combined with other datasets. In such cases, a clear separation will be made between results based on this data-analysis plan and results based on ideas that emerged later and were therefore potentially data-driven.

Pre-analysis

Our approach has been heavily informed by the work on the Dutch National Survey by Gopalakrishna et al. (2022), but there are some notable exceptions. For example, because there are no subgroups in the present study (and all participants will answer all questions), data analysis will not involve any imputation or missingness analysis. Following Gopalakrisha et al., there are no item non-responses; participants are required to answer and continue with the next questions or to withdraw from the survey. Although this approach removes the possibility of missing values, one must acknowledge that such decisions may impact the quality of the collected data. For a majority of questions participants may respond N/A if the question does not apply to them. There may be various reasons for N/A responses, but whatever these reasons, an N/A indicates that this behaviour has not been performed.

For any outcomes where N/A is a viable answer, 'not applicable' will be replaced by the lowest value 1 ('Never') (see Gopalakrishna et al., 2022). This implies that we interpret 'NA' on these items as 'behaviour has not been performed' lumping possible reasons together. Responses to the question on academic roles of influence will be recoded as binary, where 0 = 'no roles of influence', and 1 = 'at least one role of influence'.

If a survey is incomplete, either through technical error or through a participant withdrawing from the study, partial data will not be included in any subsequent analyses. Similarly, If participants show aberrant response patterns (e.g., the same ratings for all questions), or if the time taken to complete the survey is more than 60 min (which is approximately 4–5 times longer than it should take), those responses will be excluded from further analysis.

DETAILS ON PLANNED ANALYSIS

General details

1. On the Open Science Framework, a folder named 'Data Analysis' will be created containing the original data file and any associated JASP analysis files, which include the results for all subsequent analyses.
2. The main analyses will be performed independently by two members of the research team, based on the principles laid out in the registered report analysis plan. Any inconsistencies between these analyses will be discussed and resolved, after arbitration by the core research team members, if needed.
3. For regressions, where we explore any 2-way or 3-way interactions between research practices and explanatory variables, if these models converge and do not yield standard errors >100 times the corresponding regression coefficients, we will report their results.
4. The decisions on which independent variables will be included in the regression models will be described below. No automated variable selection techniques will be used.
5. Deviations from the analysis plan as stipulated will be logged by the two analysts. The same applies to decisions taken to reach consensus should the analysts reach different results.
6. All regression models (see D below) will contain a *base set* of 4 background variables coding for subdiscipline, academic rank, gender, and primary research methodology

7. Descriptive values will be calculated excluding any 'not applicable responses'
8. For regression analyses, 'not applicable responses' are recoded as 'never' (a value of 1), as in Gopalakrishna et al. (2022).

A. Descriptive statistics of the explanatory variable scales.

1. For each of the 6 explanatory variables scales, Mean scores and standard deviations for each explanatory variable are calculated (from responses to Qs 20–33)
2. We will also calculate the means and standard deviations for the explanatory variables broken down by subdiscipline, academic rank, gender, research methodology.

B. Overall descriptive statistics of outcomes.

1. Relative prevalences for scores for each responsible research practice (RRP) question (Qs1-15). Prevalence is calculated as the percentage of participants that scored 5, 6 or 7 among the participants that deemed the RRP at issue applicable.
2. Mean score and standard deviation for 15 RRPs overall.
3. Mean scores and standard deviations for each responsible research practice separately (Qs1-15)
4. Percentages who have engaged in specific practice (Q 17)
5. Percentages who have engaged in specific practice (Q 18)
6. Percentages who have engaged in specific practice (Q 19)
7. B2, broken down by subdiscipline and academic rank.

C. Descriptive statistics of the background variables.

1. Absolute counts and percentages of the 4 background factors: sub-disciplinary field (15 categories), academic rank (5 categories), gender (3 categories) and research methodology (3 categories)
2. Subdiscipline by rank (75 cells)

D. Multiple regression analyses for outcomes A5 – A8.

The table below specifies 44 regression analyses, 11 for the primary dependent variable (overall responsible research practice score), and 33 (3 × 11) for the dependent variables related to specific practices of preregistration, registered reports, and multilab collaborations. The Base Set of variables includes *subdiscipline, academic rank, gender, and research methodology*. Independent variables are mean-centred prior to regression analyses. Dependent variables are:

1. RRP mean (B2), linear model. In the multiple linear regression analysis, overall RRP mean is computed as the average score of the 15 RRPs, with the not-applicable scores recoded to 1 (i.e., 'never')
2. Engagement in specific practices (B4), binary logistic model
3. Engagement in specific practices (B5), binary logistic model
4. Engagement in specific practices (B6), binary logistic model

Table of Planned Regressions

Regression number	Independent variables	Adjustment variables	Additional notes
1		Base set	Estimate effects of base set variables
2	Explanatory variable 1	Base set	Estimate effects of explanatory variable 1
3	Explanatory variable 2	Base set	Estimate effects of explanatory variable

Regression number	Independent variables	Adjustment variables	Additional notes
4	Explanatory variable 3	Base set	Estimate effects of explanatory variable
5	Explanatory variable 4	Base set	Estimate effects of explanatory variable
6	Explanatory variable 5	Base set	Estimate effects of explanatory variable
7	Explanatory variable 6	Base set	Estimate effects of explanatory variable
8	Explanatory variables 1–6	Base set	Estimate effects of all explanatory variables simultaneously
9	Institution Type × Rank	Base set + separate variables that make up the interactions	learn if the effect of rank, if any, varies by type of institution (i.e., Russell Group, Post-92 etc.)
10	Institutional Support	Base set + explanatory variables + separate variables that make up the interactions	Learn if the effect of explanatory variables varies by institutional support
11	Roles of Influence	Base set + explanatory variables + separate variables that make up the interactions	Learn if the effect of explanatory variables varies by roles of influence

Note: Additional exploratory analyses may be conducted, and these will be noted as being unplanned prior to data collection.

APPENDIX C

Power Analysis

Although the analyses reported here are exploratory, in that we are not testing specific hypotheses, and nor are we looking for a smallest effect size of interest for any particular test, we have used G*Power (Faul et al., 2009) to estimate power/sample sizes for a range of possible effect sizes. The table below indicates the level of effect size detectable with varying sample sizes, with power of 90%, alpha set to .05, for regressions with up to 8 predictor variables. Effect sizes are rounded to 4 decimal places for f-squared values and to three decimal places for Cohen's d values. These estimates do not take into account interactions between variables, and so power for any analysis of interaction effects will be weaker, resulting in noisier estimates of effect sizes.

TABLE A1 Estimated effect minimum sizes detectable with statistical power of 90% for a range of survey sample sizes for regression analyses with 8 predictor variables.

Total sample size	Effect size f-squared	Effect size Cohen's d	Effect size r
100	0.2080	0.912	.415
200	0.0998	0.632	.3
300	0.0655	0.512	.248
400	0.0487	0.444	.217
500	0.0380	0.394	.193
1000	0.0192	0.277	.137
2000	0.0095	0.196	.098
3000	0.0064	0.160	.08
4000	0.0048	0.138	.069
5000	0.0038	0.124	.062