**Evaluating the pedagogical effectiveness of study preregistration in the undergraduate dissertation: A Registered Report**

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**Abstract**

Research shows that questionable research practices (QRPs) are present in undergraduate final-year dissertation projects. One entry-level Open Science practice proposed to mitigate QRPs is ‘study preregistration’, through which researchers outline their research questions, design, method and analysis plans prior to data collection and/or analysis. To date, no research to our knowledge has examined the effectiveness of preregistration on undergraduate students’ learning and perceptions of research practices, despite recent recommendations that preregistration could facilitate engagement and reduce anxiety with the dissertation process. In this study, we aim to empirically test the effectiveness of preregistration as a pedagogic tool in undergraduate dissertations using a quasi-experimental design. A total of 200 UK psychology students will be recruited and classified into two groups: those who preregister their empirical quantitative dissertation (*n* = 100; experimental group) and those who do not (*n* = 100; control group). Attitudes towards statistics and QRPs and understanding of Open Science practices will be measured both pre- and post-dissertation. Exploratory measures include participant’s capability, opportunity and motivation (COM-B) to engage with preregistration, measured at Time 1 only. In line with/contrary to hypotheses, study preregistration [significantly/did not significantly increased/reduced] positive attitudes towards statistics, acceptance of QRPs, and perceived understanding of Open Science. Exploratory analyses indicate that preregistration was associated with [greater/less/no difference] capability, opportunity and motivation and qualitative responses revealed that preregistration [XXX]. These results contribute to timely discussions surrounding the utility of embedding Open Science principles into research training.

**Keywords:** Preregistration, Open Science, reproducibility, undergraduate training, dissertations; research training

**Evaluating the pedagogical effectiveness of study preregistration in the undergraduate dissertation: A Registered Report**

In recent years, psychology has put reproducibility, replicability, and transparency at the forefront of the research agenda (Asendorpf et al., 2013; Munafò et al., 2017; Open Science Collaboration, 2015). Fuelled by replication concerns in the general scientific literature, an era of ‘Open Science’ has prompted a plethora of ideas and recommendations to envision a new future for science (Pashler & Wagenmakers, 2012). A move to study preregistration, open materials, and open data are proposed to combat *questionable research practices* (QRPs; John et al., 2012) that plague the literature, such as *p*-hacking (Head et al., 2015), ‘Hypothesising After Results are Known’ (HARKing; Kerr, 1998), and selective reporting (John et al., 2012) or ‘undisclosed flexibility’ (Simmons et al., 2011). Furthermore, an incentive shift to high-quality, *slow* science is picking up momentum (Frith, 2020). Despite these practices being increasingly endorsed and embraced by the scientific community (however, see Szollosi et al., 2019 for an alternative perspective), scant research assesses the pedagogic value of Open Science practices in improving teaching and learning.

Importantly, much of the recent shift to Open Science practices has been championed by grassroots, collaborative initiatives (e.g., see Button et al., 2020; Pownall, 2020b). In recent years psychologists have developed initiatives such as the Society for the Improvement of Psychological Science (SIPS; [https://improvingpsych.org](https://improvingpsych.org/mission/)), the open source reporting forum PsychDisclosure (LeBel et al., 2013), and the early career researcher-led journal club, ReproducibiliTea (Orben, 2019), all with the aim of improving the rigour and reproducibility of psychological science. Beyond these, organisations and initiatives are centred around the improvement of psychological science, stressing the importance of rigorous, robust methods (e.g., Crüwell et al., 2019; Munafò et al., 2017; Simmons et al., 2011; Tennant et al., 2016; Wagenmakers et al., 2012). For example, Klein et al. (2018) note the importance of preparing and sharing research in a way that values transparency and note how this can be done incrementally to improve research efficiency and credibility. Similarly, Devezer et al. (2020) focus on recommendations to improve methodological problems in science reform, such as the adoption of a formal approach that embeds statistical rigour and nuance into science reform.

**Open science in undergraduate training**

The recent shifts towards novel and creative ways of promoting uptake of Open Science practices offer the opportunity to reevaluate core aspects of undergraduate training, as well as wider scientific research practices. For example, there have been some emergent initiatives that have specifically concentrated on how to embed teaching on the ‘Replication Crisis’ and Open Science practices into undergraduate teaching (e.g., Button et al., 2016, 2018; Chopik et al., 2018; Frank & Saxe, 2012; Janz, 2016). There has also been a keen interest in interventions to improve understanding of QRPs in, for example, graduate psychology training (Sacco & Brown, 2019; Sarafoglou et al., 2020). However, the impact that these have on students’ learning and perceptions is yet to be empirically investigated.

**The value of preregistration**

One method of reducing QRPs and enhancing research transparency is study preregistration. Study *preregistration* comprises a time-stamped, uneditable protocol that transparently outlines a study’s research questions, design, hypotheses, methods, and analysis plan prior to data collection and/or analysis (Nosek et al., 2018; van't Veer & Giner-Sorolla, 2016). The process of preregistration encourages researchers to plan the decisions that have traditionally been made after data collection (e.g., exclusion criteria, analysis details) beforehand, using a wide host of platforms such as the Open Science Framework (<https://osf.io/>) and AsPredicted (<https://aspredicted.org/>). Preregistration increases transparency about the authors’ original intentions (LeBel & Peters, 2011) and should, in theory, limit selective reporting of results (Nuzzo, 2015).

Here, we propose that preregistration is one entry-level way of establishing a level of rigour and robustness into the undergraduate dissertation process (as per Pownall 2020a). The potential value of preregistration in this context has been noted by educators. For example, the Framework of Open and Reproducible Research Training (FORRT; www.forrt.org) includes preregistration as one of the six pillars of effective reproducibility training, including at the undergraduate level. Others have suggested that “most study programmes should offer easy ways of implementing preregistration in empirical research seminars” (Olson et al., 2019; p 13), due to the potential for preregistration to promote “critical reflections of research practices” and improve student’s statistics literacy (Olson et al., 2019, p. 13). As Pownall (2020a) also argues, the process of embedding preregistration of undergraduate dissertations largely complements current practices in dissertation supervision. Sacco and Brown (2019) note that preregistration is thus useful when conducting research with the view to publish the results with undergraduate students (see also Blincoe & Buchert, 2020). In this study, we examine the value of study preregistration in the undergraduate curriculum to assess whether this can improve attitudes towards statistics (e.g., students’ perceived difficulty of statistics, value of statistics, and perceived competence in statistics) and QRPs, as well as students’ perceived understanding of Open Science.

***The undergraduate dissertation***

In the UK, final-year psychology dissertations consist typically of an independent empirical project that require students to design a protocol, collect data, and analyse the results. According to the accreditation standards of the British Psychological Society (2019) undergraduate psychology dissertations in the UK require students to “individually demonstrate a range of research skills including planning, considering and resolving ethical issues, analysis and dissemination of findings” (p. 13). Final-year projects are thus typically self-contained research studies that are constrained by the scope and availability of resources but are supervised closely by an experienced academic. Much pedagogic research has demonstrated that, given the level of autonomy that students have over their final-year dissertation, students typically struggle with some of the components of this mandatory part of their degree. For example, it is reported widely that undergraduate students face anxiety, disengagement, and stress related to their final-year dissertation (e.g., Devonport & Lane, 2006). Indeed, research shows that undergraduate students often experience difficulty with their dissertation, due to pedagogic issues such as debilitating statistics anxiety (e.g., Onwuegbuzie & Wilson, 2003), under-confidence with their writing ability (Greenbank et al., 2008) and challenges navigating supervisory relationships (Day & Bobeva, 2007).

Contemporary research also indicates that QRPs are prevalent within undergraduate research projects (Krishna & Peter, 2018; Kvetnaya et al., 2019; Sorokowski et al., 2019). For example, Krishna and Peter (2018) assessed the prevalence of QRPs in final-year undergraduate dissertations and found that students typically engage in QRPs related to reporting and analysing their results. Similarly, Olson et al. (2019) studied the prevalence of QRPs of taught masters students’ theses and found inconsistency of *p*-value reporting, although it was not clear that this was a result of intentional *p*-hacking. Research outside of psychology also indicates that from dissertation to publication, the ratio of supported to unsupported hypotheses more than doubles (O’Boyle et al., 2017). Recently, there has been a focus on addressing QRPs that feature in undergraduate final-year projects through consortia-based approaches (Button et al., 2020; Kvetnaya et al., 2019; Munafò et al., 2017) and through focusing on replication studies with undergraduate projects (e.g., de Leeuw et al., 2019; Jekel et al., 2020).

The use of QRPs in the undergraduate dissertation likely stems from many different sources: resource and time constraints mean that many undergraduate experiments are typically underpowered (Button et al., 2016; 2018), students perceive that there is a pressure from supervisors to ‘find’ significant results, which are more likely to lead to a publication (Wagge et al., 2019), and in our own experience, worry that a ‘lack of significant’ results will adversely affect their grades. QRPs may also stem from a lack of awareness that they are problematic (e.g., Banks et al., 2016). This is related to the pressures put on academics to publish novel, positive results (Franco et al., 2014), due to the ‘publish or perish’ culture that pervades academia (Grimes et al., 2018) that might filter down to their students. Indeed, an undergraduate publication is seen as an advantage when applying for highly competitive places on taught masters and doctoral training (Button, 2018). If these studies are then selectively published, they contaminate the scientific literature with unreliable results. Understanding undergraduate students’ use and acceptance of QRPs is useful, given that students’ research behaviour reflects the quality of Open Science teaching and adoption of rigorous practices more broadly (Olson et al., 2019). Some emergent research has begun to investigate the research practices of early-career researchers (Nicholas et al., 2017), including uptake of Open Science practices (Stürmer et al., 2017).

 Importantly, consideration of the prevalence of QRPs in the undergraduate dissertation has led to interventions to reduce them. Button et al. (2020), for example, describe and evaluate an approach to improving rigour of undergraduate dissertations via a consortium approach to science. This approach also echoes Detweiler-Bedell and Detweiler-Bedell’s (2019) team-based approach to undergraduate research supervision. Creaven et al. (2021) stress the importance of embedding a concern for rigour, transparency, and openness into the undergraduate dissertation, stressing how the undergraduate dissertation should be thought of as an important learning activity that offers many pedagogical benefits to students. Similarly, Blincoe and Buchert (2020) propose that preregistration may be a useful pedagogical tool for undergraduate psychology students. Despite some useful and recent conversations that discuss the *need* to embed an Open Science approach into undergraduate research training (Button et al., 2020; Creaven et al., 2021; Pownall, 2020), an *empirical* exploration into how Open Science practices in undergraduate dissertations may benefit (a) students, and (b) the Open Science movement has been notably absent from these conversations. Indeed, while much work has considered how to promote uptake of preregistration practices of early career (Zečević et al., 2020) and more established researchers (Kidwell et al., 2016; Munafò et al., 2017), little research has explicitly focussed on the utility of preregistration for undergraduate students’ research practices, despite recommendations that preregistration could facilitate engagement with the dissertation process (e.g. Nosek et al, 2018), reduce statistics anxiety, and improve students’ experience of their dissertation (Creaven et al., 2021; Pownall, 2020a).

**The present study**

We aim to investigate empirically the pedagogical effectiveness of preregistration in undergraduate dissertation provision; that is, how the process of preregistration may be useful at tackling some of the core pedagogical challenges that students face in their dissertation research (including statistics anxiety) whilst also considering how engaging with the process of preregistration can aid understanding of Open Science issues more generally. Our core research questions aim to evaluate whether preregistration is a useful pedagogic practice to improve students' attitudes towards statistics, awareness of QRPs, and perceived understanding of Open Science in this cohort. To achieve this, we will employ a 2 (Group: preregistration vs. control) x 2 (Time: time 1 pre-dissertation vs. time 2: post-dissertation) mixed design, with Group as the between-participants and Time as the within-participants factor. We have three confirmatory hypotheses based on a significant two-way interaction between Group and Time. For all of the hypotheses, we predict a significant Time\*Group *interaction*, in that participants in the preregistration group will show improvements above and beyond those that occur due to time differences (Time 1 vs Time 2).

**H1:** Due to the thoughtful engagement with statistical processes that the preregistration process requires (Lindsay et al., 2016), we predict that students who preregister their dissertation will have higher scores on the four constructs within the Survey of Attitudes Toward Statistics (SATS-28), from Time 1 to Time 2.

**H1a.** Students who preregister their dissertation will have higher (i.e., more positive) *affect* towards statistics compared to students who do not preregister their dissertation from Time 1 to Time 2.

**H1b**. Students who preregister their dissertation will have higher self-reported *competence* with statistics compared to students who do not preregister their dissertation from Time 1 to Time 2.

**H1c**. Students who preregister their dissertation will have higher perceived *value* of statistics compared to students who do not preregister their dissertation from Time 1 to Time 2

**H1d**. Students who preregister their dissertation will have higher and less *difficulty* with statistics at T2 compared to students who do not preregister their dissertation from Time 1 to Time 2.

**H2:** Secondly, given that the preregistration process prompts wider consideration of the QRPs that preregistration aims to avoid, we predict that students who preregister their undergraduate dissertations will have a reduced self-reported acceptance of 11 selected QRPs compared with students who do not preregister their dissertation, when comparing Time 1 responses with Time 2.

**H3:** Relatedly, given that the preregistration process forms part of a wider conversation about open and transparent science, we expect that students who preregister their undergraduate dissertations will have higher perceived confidence in their understanding of 12 selected Open Science terminology terms, compared with students who do not preregister their dissertation, when comparing Time 1 responses with Time 2.

Finally, as an exploratory measure with no predetermined hypotheses, we will also assess students’ Capability, Opportunity and Motivation (COM-B) towards preregistration at Time 1 and qualitative responses regarding the perceived barriers and facilitators of preregistration at Time 2.

**Method**

**Transparency Statement**

All materials and data will be publicly available via the Open Science Framework: <https://osf.io/8sndy/> and our study meets Level 6 of the PCI RR bias control (<https://rr.peercommunityin.org/help/guide_for_authors>). In the sections that follow, we report all measures, manipulations, and exclusions.

**Design & Participants**

The study comprises a 2 (Group: preregistration vs. control) x 2 (Time: pre-dissertation vs. post-completion) mixed factors design. To be eligible for inclusion, participants are required to confirm that they are a final-year undergraduate student, studying Psychology at a UK institution and planning an empirical quantitative undergraduate dissertation. Participants must have not already pre-registered their proposed undergraduate study at Time 1 and must confirm this in the beginning of the study. This is to ensure that the study can contribute directly to existing pedagogic policy discussions regarding embedding Open Sciences within the undergraduate dissertation (e.g. the British Psychological Society’s course accreditation standards, 2019). To be eligible to participate at Time 2, participants must have completed Time 1 (and have a corresponding participant ID number to match up responses).

Our planned sample size is based solely upon resource and time considerations including the time window for participant recruitment and available funds for participant compensation (see Lakens, 2021). Two-hundred and forty final-year undergraduate Psychology students will be initially recruited with approximately 20% attrition expected at Time 2 based on prior research sampling from online platforms (Palan & Schitter, 2018). The final planned sample size is therefore 200 participants, with an experimental group of approximately 100 having initiated a preregistration of their final year quantitative project and a control group of 100 not initiating a preregistration. Simulation based power analyses conducted using the superpower shiny package (Lakens & Caldwell, 2021; https://arcstats.io/shiny/anova-exact/) with 10,000 simulations indicate that this sample size will have 80% statistical power to detect a moderate effect size for the two-way interaction between Group and Time (*np2* = .04), as well as a small-moderate effect of *d* = .40 for the focal pairwise comparison between preregistration vs. control at Time 2 (Code/Output can be accessed here: <https://osf.io/y9vz7/>).

Our final sample comprised XXX participants (Mage = , SD = % female, % White British). Sensitivity power analyses conducted on thisfinal sample size indicate that we achieved XX power to detect effects of > .XX, which was higher/lower than planned. All participants will provide informed consent. Ethical approval has been granted from the University of Leeds School of Psychology Ethics Committee on 8th July 2021 (Reference: PSYC-266; https://osf.io/5rtch/).

**Recruitment Plan**

We will purposefully sample students via Prolific Academic (using custom pre-screening), university participant pools (SONA) and through social media adverts, ensuring they meet the inclusion criteria. Inclusion criteria will be included in all recruitment materials and participants will confirm they meet this in the first page of the study’s procedure, via check-list boxes. After reading a brief definition of preregistration, participants will be asked to confirm at Time 1 and 2 whether they have preregistered their undergraduate dissertation or not. We will use ‘Cross Logic Quota’ sampling within Qualtrics (see Qualtrics, <https://www.qualtrics.com/support/survey-platform/survey-module/survey-tools/quotas/>) to roughly monitor group allocation at Time 1, although this will be done using the preregistration *plan* questions (see below), which could differ from the final preregistration group allocation at Time 2 (i.e., some participants could plan to preregister but do not actually preregister at Time 2). Because preregistration is typically at the supervisor’s discretion, and not widely implemented within undergraduate degree programmes, we will also engage in targeted recruitment to the preregistration condition through appropriate Open Science teaching channels: these include organisational stakeholders such as the UK Reproducibility Network and the BPS, as well as UK institutions who incorporate preregistration as part of their undergraduate curriculum (see Table 1). We will also use social media channels to recruit participants. All participants recruited via Prolific Academic will be paid the equivalent of £6.50 per hour for their time; participants will be paid the equivalent of £6.50 per hour at each timepoint, with completion time of each estimated to be 15-20 minutes. Participants recruited via Prolific will be contacted for Time 2 via Prolific’s ‘contact participants’ function, participants recruited elsewhere will be contacted via email.

*Table 1.* Potential universities for student recruitment who offer preregistration within the final-year curriculum.

|  |  |
| --- | --- |
| **University** | **Preregistration approach** |
| Bath Spa University | Students complete an internal preregistration in Semester 1. |
| University of Glasgow  | Open Science forms an integral part of core undergraduate teaching. |
| Royal Holloway University  | Internal preregistration is embedded into dissertation supervision. |
| Durham University  | Internal detailed preregistration forms part of the final-year dissertation module. |
| Undergraduate consortium approach (see Button et al., 2016) | The Universities of Bath, Cardiff, Aston, Liverpool and Bristol run group consortia projects through which students’ preregister their final year project.  |

**Procedure**

Data will be collected online using Qualtrics (<https://www.qualtrics.com/uk/>) through the various recruitment strategies above. At Time 1, participants will be enrolled for their final year but will not have initiated their dissertation project nor their preregistration (September - November 2021). This will provide a baseline in which to compare responses at Time 2 (post-dissertation; May-July 2022).

Participants will first provide demographic information (age, gender, ethnicity, institution of study) before confirming that they are in the final year of their BSc undergraduate psychology degree and plan to undertake a *quantitative* dissertation project in the 2021-2022 year (“yes/no”). Participants who answer ‘no’ will be informed that they do not meet the inclusion criteria for the study. We will then collect data related to students’ self-reported academic attainment in the mandatory statistics module of their degree in second year and their average grade in the second/penultimate year of their degree. This will be scored on a categorical scale that is in line with the UK conventions of academic grades awarding: 1st class classification (> 70%), 2:1 classification (60 - 69%), 2:2 classification (50 - 59%), 3rd class classification 40 - 49%, fail (< 40%). This is to control for potential baseline differences between our two groups.

Participants will then be provided with a brief definition of preregistration, adapted from Lindsay et al. (2016): “*Preregistering a research project involves creating a record of your study plans before you look at the data. The plan is date-stamped and uneditable. The main purpose of preregistration is to make clear which hypotheses and analyses were decided on before you have accessed your data and which were more exploratory and driven by the data.”* Then, to ensure participants have not yet preregistered their project at Time 1, we will ask participants whether they *plan* to preregister their undergraduate dissertation (yes/no/unsure) and whether the undergraduate dissertation has already been preregistered (yes/no). All participants at Time 1 will then answer the same measures. The items related to participants’ plans will not be used to categorise participants into groups, instead it will be used to guide quota sampling.

***Measures (Time 1)***

***Survey of Attitudes Toward Statistics (SATS-28).*** To assess whether preregistration improves attitudes towards statistics, students will complete the Survey of Attitudes Toward Statistics (SATS-28). This 28-item scale includes items related to statistics affect (e.g. “I am scared by statistics”), cognitive competence (e.g. “I can learn statistics.”), value (e.g. “Statistics is worthless”) and difficulty (e.g. “Statistics is highly technical”). These items are scored on a 1 *(Completely disagree)* to 7 *(Completely agree)* Likert Scale and 19 items are reverse scored. A total score will be computed for each of the subscales of the Survey of Attitudes Toward Statistics (SATS-28): statistics affect, cognitive competence, value, and difficulty. Reverse scored items will be re-coded so that higher scores indicate: more positive affect, higher competence, higher value and lower difficulty. This scale has been found to have acceptable internal reliability (Cronbach α 0.64-0.85 for each of the subscales; Dauphinee et al., 1997) and for the scale as an overall index (*a* = 0.91; Ayebo et al., 2020). The internal reliability of each subscale was poor/adequate/excellent (*Cronbach’s a,* affect *=* XX, competency = XX, value = XX, difficulty,= XX) in the current study.

***Acceptance of QRPs.*** To assess whether preregistration influences attitudes towards QRPs, students will rate their views on 15 research decisions (11 of which are QRPs, 4 of which are neutral/acceptable) on a sliding scale from 1 (*Sensible*) to 7 (*Problematic*; Krishna & Peter, 2018). These include items such as “selectively reporting studies” and “deciding to exclude data after looking at results” (QRPs) and “reporting effect sizes” (neutral/acceptable). The ‘neutral/acceptable’ items will not be analysed but will mask the nature of this questionnaire. We will compute all 11 items pertaining to QRPs into one total indicating general acceptance of QRPs, where higher scores indicate less acceptance of QRPs. The internal reliability of this questionnaire was *poor/adequate/excellent* (*a* = XX) in the current study.

***Perceived* *Understanding of Open Science.*** As per other literature (Krishna & Peter, 2018’ Stürmer et al., 2017), to test perceived understanding of Open Science practices and terminology, students will indicate their confidence in their ability to understand 12 key terms (e.g. Replication Crisis, *p*-hacking, open data, file drawer effect) on a 1 (*Not at all confident*) to 7 (*Entirely confident*) Likert scale. These concept recall items will be compiled into a total score of Open Science perceived understanding. The internal reliability of this questionnaire was *poor/adequate/excellent* (Cronbach's *a* = XX) in the current study.

***Attention and bot checks.*** As an attention check (i.e., to ensure that participants are actively paying attention to the survey materials and to prevent spam/bot respondents), we will add an item “*Please select strongly disagree to this question*” in the COM-B measure, to assure data quality. This will be repeated in Time 1 and Time 2. As a second attention check, we will use a protocol from the Prolific guidelines and will ask participants “Please enter the word *‘purple’* in the textbox below.” accompanied by a textbox. Any participant who fails both of these attention check (i.e., who does not select strongly agree and correctly enter the word ‘purple’) will be excluded from the final analyses. We will also employ Qualtrics’ ‘prevent multiple submissions’ and ‘prevent indexing’ (i.e., block search engines from including the study URL in search results) security options to minimise chances of fraud/bot responses.

**Exploratory Measures**

***Capability, Opportunity and Motivation (COM-B) towards preregistration.*** In line with Norris and O’Connor (2019), we will also apply a behaviour change approach to assess the facilitators and barriers to study preregistration at Time 1 only. The COM-B model (Michie et al., 2011) posits that a behaviour occurs only if an individual has sufficient Capability, Opportunity and Motivation to perform it. Capability includes psychological capability (i.e., knowing how to perform the behaviour) and physical capability (i.e., being physically able to perform the behaviour). Opportunity includes social opportunity (i.e., being around others who are performing the behaviour) and physical opportunity (i.e., having the time and resources to perform the behaviour). Motivation includes reflective motivation (i.e., plans and beliefs to perform the behaviour) and automatic motivation (i.e., desires, impulses and inhibitions towards the behaviour; Michie et al., 2011). The brief measure of COM-B developed by Keyworth et al. (2020) will be employed. This measure contains 6 items, where one item addresses each of the six components of the COM-B on a 11-point Likert scale ranging from 0 (*Strongly disagree*) to 10 (*Strongly agree*). Each item is accompanied by an explanation of what the COM-B component referred to in the questions means. For example, ‘*I have the PHYSICAL opportunity to preregister my undergraduate dissertation*’ is accompanied by the explanation defined by Keyworth et al. (2020) ‘*What is PHYSICAL opportunity? The environment provides the opportunity to engage in the activity concerned (e.g sufficient time, the necessary materials, reminders)*’. A total score will be computed for each subscale. The internal reliability of these items was *poor/adequate/excellent* (Cronbach's *a* = XX) in the current study. This exploratory measure was chosen in order to explore how a behaviour change model may be applied to engagement in Open Science practices (e.g., as per Norris & O’Connor, 2019).

**Post-dissertation (Time 2)**

The same sample of students will be asked to complete all of the above measures, except for the COM-B, again at Time 2, which represents a follow-up after their dissertation is completed in approximately May 2022. At Time 1, participants reported whether they planned to preregister their dissertation, and at Time 2, participants will first report whether they did actually preregister [yes/no]. Participants’ responses to this question at Time 2 will be used to allocate participants to the 'preregistration' vs. 'no preregistration' groups. For example, if a participant responded at Time 1 that they planned to preregister but at Time 2 they did not, they will be allocated to the ‘no preregistration’ control group for the final analyses. At Time 2, we will also ask participants who preregistered to self-report the extent to which they followed their preregistration plan (*1 = not at all, 2 = somewhat, 3 = entirely*) and this data will be used descriptively to describe our sample.

 In addition, participants will also be asked four questions assessing whether they have implemented other Open Science practices associated with their dissertation: (1) creating an Open Science Framework account, (2) uploaded material (*open material*), (3) code/scripts (*open code*), and (4) data (*open data*) to a public archive. This will be used descriptively to gain more insight into other contextual factors that are associated with preregistration. Qualitative responses of students’ experiences of the preregistration process, including enablers and barriers, will also be collected through three-open ended questions asking: “Please list all of the advantages you perceive of preregistration”, “Please list all of the disadvantages”, and “Do you see any barriers to preregistration?”.

***Perceptions of supervisory support.*** Finally, due to the literature that suggests that perceived supervisor support affects students' experiences of their dissertation research (Roberts & Seaman, 2018), to assess students’ perceptions of their supervisory support at Time 2, we will use a 14-item measure of perceptions of supervisor support. This scale includes items such as “*I am satisfied with the support I have received from my supervisor*” and “*My supervisor was knowledgeable about research design/process as related to my project*.”. One item will also be “*I felt pressure from my supervisor to find significant results in my dissertation*” (reverse scored). These are measured on a 1 (*Strongly disagree*) to 5 (*Strongly agree*). These will be computed into one overall score of supervisory support and used as a covariate in further analyses.

**Risk and Mitigations**

We acknowledge certain risks associated with our study and aim to mitigate these with the following measures. The first risk is participant attrition from Time 1 to Time 2, leading to incomplete data across measures. We aim to mitigate this by accounting for average attrition rates in our planned sample as per other longitudinal studies conducted on Prolific (7%-24%; Palan & Schitter, 2018) and utilising a varied recruitment approach. At Time 2, participants not recruited via Prolific will be entered into a prize draw in order to incentivise participation. Similarly, recruitment of the preregistration group requires a level of buy-in from institutions that embed a preregistration model into their undergraduate dissertation process. Members of the research team have contacts with these institutions listed in Table 1, which should mitigate barriers to student access in the preregistration group. If we fail to reach the target sample size of 200 students, we will run sensitivity power analyses on the complete data that we do have and use this to contextualise our discussions and interpretation of final results.

We have also factored in discrepancies in definitions of preregistration practices, by providing all students with a student-friendly, accessible definition of preregistration from the literature (Lindsay et al., 2016). This should mean that students are able to readily identify whether they engaged in this specific process, above and beyond other processes within the dissertation timeline (e.g., discussing a protocol with their supervisor or writing an ethics application). By asking students to confirm at Time 2 that they have preregistered their study, this should also alleviate any problems with students erroneously being allocated to the wrong condition at Time 1.

Finally, our study may have confounding variables that we aim to reduce. For example, it is likely that institutions that actively embed preregistration into the dissertation process may also teach Open Science practices more generally within their curriculum, which may be a confound when evaluating the effectiveness of study preregistration. This will first be checked by establishing whether there are differences in students’ Open Science attitudes and knowledge at Time 1. Secondly, we mitigate this by investigating the *interaction* between Group and Time on all of our outcome variables. Specifically, we expect that despite any differences between groups at Time 1, there will be a significant interaction indicating that engaging with the preregistration process has an *additive* effect on students’ attitudes, behaviours, and perceptions of Open Science (i.e., it improves scores beyond improvement that occurs due to differences in time point).

It could also be feasible for ceiling effects to occur in the preregistration group at Time 1, particularly given the aforementioned concern about contextual factors that impact students’ knowledge of Open Science and QRPs. This could mean that differences from Time 1 to Time 2 are ‘masked’ due to high scores at Time 1 for the preregistration group. Whilst we cannot methodologically mitigate this concern, we will discuss it in detail following data collection and use this to guide interpretation of our results.

Finally, we will avoid missing data adversely impacting our statistical power by using a ‘requested entry’ option on Qualtrics, so participants are unable to progress in the survey without first confirming that they are happy that they have answered all the questions they wish to (if some are left unanswered).

**Analysis Strategy**

A total of X participants were excluded from analyses due to failing the attention check. Baseline characteristics of perceived supervisory support and prior statistics attainment did not significantly differ/significantly differed between the preregistration and control group (see Table 2).

Table 2.

*Baseline characteristics between the preregistration and control groups (mean and standard deviation).*

|  |  |  |
| --- | --- | --- |
|  | Preregistration | Control |
| Perceptions of Supervisor |  |  |
| Prior statistics attainment |  |  |

A series of 2 (Group: preregistration vs control) x 2 (Time: time 1 vs. time 2) mixed ANOVAs will be conducted on attitudes towards statistics (SATS-28; H1), attitudes towards QRPs (H2), and perceived understanding of Open Science (H3). Any baseline differences between groups on perceptions of supervisor and prior statistics attainment will be entered as a covariate in these analyses (ANCOVA). Bonferroni corrections will be applied to elucidate pairwise comparisons, with statistical significance denoted at *p* < .05. Bayes factors will be calculated for all analyses to evaluate strength of evidence (Dienes, 2011). In line with recommendations for early research (Schönbrodt et al., 2017), we will consider BF10 > 6 as evidence for the alternative hypothesis. Bayes factors will also be used to evaluate any null results with BF10 < 0.17 considered as evidence for the null hypotheses. There is no previous literature to guide an informed prior, and thus Bayesian analyses will be computed using the default JZS prior (r = 0.707; Rouder et al., 2009) in JASP (JASP Team, 2020). The JZS prior is a noninformative default and objective prior designed to minimise assumptions about the expected effect size.

As an exploratory analysis, we will also conduct a between-participants *t*-test on Time 1 responses to the capability, opportunity and motivation (COM-B) questionnaire, to assess enablers and barriers to preregistration between the preregistration and no preregistration group.

**Table 3.** Research questions, accompanying hypotheses, and analysis plan

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Research question** | **Hypotheses** | **Sampling plan** | **Analysis plan** | **Rationale for deciding the sensitivity of the test for confirming or disconfirming the hypothesis** | **Interpretation given different outcomes** | **Theory that could be shown wrong by the outcomes**  |
| 1. Is preregistration a useful pedagogic practice to improve students' perceived understanding of research methods and statistics in the undergraduate dissertation?
 | We generally predict that attitudes to statistics will improve over time as a result of engaging with the third-year dissertation process itself, but that preregistration will have an additive effect on this. Students in the preregistration group will show a marked improvement compared to those in the control (H1) | Two-hundred and forty final-year undergraduate Psychology students will be initially recruited with approximately 20% attrition expected at Time 2 based on prior research sampling from online platforms (Palan & Schitter, 2018). The final planned sample size is therefore 200 participants. See design and participants for power analysis in more detail.  | 2 (Group: preregistration vs control) x 2 (Time: time 1 vs. time 2) mixed ANOVA with attitudes to statistics as the dependent variable. | Simulation based power analyses conducted using the superpower shiny package (Lakens & Caldwell, 2021) with 10,000 simulations indicate that this sample size will have 80% statistical power to detect an effect size of *np2* = .04 for the two-way interaction between Group and Time, and 80% power to detect small-moderate effects of *d* = .40 for the focal pairwise comparison between preregistration vs. control at Time 2 (Code/Output: <https://osf.io/y9vz7/>).We will also run a sensitivity analysis to compare our achieved sample size with planned sample size (see Participants and design section for further details). For our Bayesian analyses, we will adopt a F10 < 0.17 as evidence for the null, which is a conservative criteria for this analysis that will allow us to test support for the null or alternative hypothess.  | This could find that preregistration *does* impact students’ statistics attitudes, as we predict, or it could suggest that preregistration does not add benefits above and beyond differences that occur due to time (from time point 1 to time point 2). No main effect of time would suggest that students do not change in their attitudes towards statistics as they progress through their academic studies in final year. However, our bayesian analyses will also reveal the *strength of evidence* we have to make these conclusions.  | Theoretically, the notion that preregistration confers a tangible, pedagogical benefit to students in their dissertation process could be (un)supported by all of our proposed analyses. Explanations for all results will be presented in the discussion. |
| 1. Does the process of preregistration enhance awareness and acceptance of questionable research practices (QRPs)?
 | We predict that preregistration will reduce acceptance of QRPs as ‘sensible’ for the preregistration compared to the control group (H2).  | 2 (Group: reregistration vs control) x 2 (Time: time 1 vs. time 2) mixed ANOVA with acceptance of QRPs as the dependent variable. | Similarly, this analysis tests whether a preregistration process improves students’ awareness of QRPs; therefore, this analysis could find that preregistration *does* positively impact students’ awareness of QRPs, as we predict, or it could suggest that preregistration does not add benefits above and beyond differences that occur due to time (from time point 1 to time point 2).  |
| 1. Does the process of preregistration improve perceived understanding of Open Science practices?
 | We predict that preregistration will improve perceived understanding of Open Science practices and terminology compared to the control group (H3). | 2 (Group: reregistration vs control) x 2 (Time: time 1 vs. time 2) mixed ANOVA with awareness of Open Science practices as the dependent variable.  | As above, this analysis allows us to test whether preregistration improves students’ perceived understanding of Open Science practices. Similar to the above, a significant main effect of Group would indicate that preregistration does or does not impact students’ Open Science perceived understanding, independent from time effects.Interactions of the ANOVA could find that preregistration *does* positively impact students' perceived understanding of Open Science , as we predict, or it could suggest that preregistration does not add benefits above and beyond differences that occur due to time (from time point 1 to time point 2).  |
| 1. Do students recognise the benefits of the preregistration process in their undergraduate dissertation and are there any barriers/challenges to its implementation?
 | This research question is exploratory. We will first explore whether preregistration is associated with *Capability, Opportunity, and Motivation* (COM-B) *for preregistration* by comparing the preregistration.We will then conduct qualitative content analysis on participants’ free-text responses at Time 2. | This research question is exploratory and the same sample detailed above will be used to address this question.  | A t-test comparing preregistration group vs control group at Time 1 with COM-B scores as the dependent variable.Qualitative analysis using qualitative content analysis for free-text responses.  | This research question is exploratory. Qualitative research typically does not share concerns of generalisability with quantitative research, so our planned sample size for this study will be sufficient for our qualitative research question, given the epistemological underpinnings of this approach.  | This set of exploratory analyses allows us to test whether students have the sufficient capability, opportunity, and motivation to complete preregistration. Qualitative analyses will shine light into whether students recognise any barriers or challenges, in order to provide more nuance to the quantitative analysis.  |

***Attitudes Toward Statistics***

We predict that there will be a main effect of time, in that over time students’ perceptions of statistics will improve (i.e. their scores on this scale will go down) in both groups (see Table 3). We also predict that there will be a two-way interaction between Group and Time with the preregistration condition exerting an *additive* effect on this to show more marked improvement in statistics attitudes. In line/contrary to hypotheses, there was a [significant/no significant] main effect of Group and Time, and a [significant/non-significant] two-way interaction between Group and Time on *statistics affect/cognitive competency/value/difficulty*. Pairwise comparisons indicate that...

***Attitudes towards QRPs***In line/contrary to hypotheses, there was a [significant/no significant] main effect of Group and Time, and a [significant/non-significant] two-way interaction between Group and Time on attitudes towards QRPs. Pairwise comparisons indicate that...

Perceived ***Understanding of Open Science***

We expect that there will not be main effect of time; that is, participants who have not preregistered will not show an improvement in Open Science perceived understanding. We predict an preregistration Group \* Time interaction, whereby participants in the preregistration group will improve their perceived understanding from Time 1 to Time 2. In line/contrary to hypotheses, there was a [significant/no significant] main effect of Group and Time, and a [significant/non-significant] two-way interaction between Group and Time on perceived understanding of Open Science. Pairwise comparisons indicate that…

**Exploratory Analyses
COM-B**A between-participants t-test between preregistration and no preregistration Group indicated a [significant/no significant] main effect of Group on *Capability, Opportunity, and Motivation for preregistration.* Those in the preregistration group showed... compared to the control.

**Qualitative analysis**

Students’ responses to the open-ended questions at Time 2 will be analysed using thematic analysis (Braun & Clarke, 2006), in order to identify barriers and facilitators of preregistration in students (see research question 4 above). This will involve one author reading and coding the free-text responses for their content before discussing potential codes with the rest of the authorship team. The first author, in consultation with the rest of the research team, will then generate themes and subthemes for the data. This will allow an exploratory investigation into students’ first-hand accounts of the barriers (i.e., disadvantages) and facilitators (i.e., advantages) to preregistration.

**Discussion**

[Note that here, we will discuss our results as they relate to the utility and effectiveness of embedding preregistration into the undergraduate dissertation process.]

**Implications for Open Science**

 This study has much to contribute to the Open Science movement, because it is the first study, to our knowledge, that considers how one entry-level Open Science tool may be useful at tackling some of the challenges that undergraduate students face in their dissertation research process. For example, if our results find, for example, that students who are supported to preregister their dissertation have better, more positive attitudes towards statistics (i.e., they feel more confident in their ability to do statistics, they value statistics more, they see it as less difficult, and they feel more positive towards doing statistics), then this provides one way to alleviate the debilitating effect that statistics anxiety has on students during their degree. Preregistration may also have benefits beyond those that are captured in the measures of the present study. For example, engagement in the preregistration process may likely improve students’ trust in the research they are conducting, inspire ambitions to pursue a career in research, and improve research literacy above and beyond attitudes towards statistics. These potential variables are all worthy of follow-up studies that further interrogate how preregistration, and indeed Open Science tools more broadly, may confer advantages to undergraduate students.

Further, this study also has vast implications for the field of Open Science too. Supporters of the Open Science movement have eloquently and convincingly made the moral and theoretical argument for embedding Open Science within undergraduate teaching and supervision. However, there is a notable lack of empirical research which gathers data in order to assess whether students actually benefit from engagement with these practices. To our knowledge, this study is the first to use quasi-experimental methods to begin to investigate this research question.

**Limitations**

There are certain limitations that we recognise prior to data collection. For example, students and supervisors who develop a detailed, rigorous preregistration and engage in the process more with their supervisor might report greater benefits compared to those who develop a poor quality, less detailed preregistration. Indeed, there is emerging literature to suggest that the specificity of preregistrations differs between researchers (Bakker et al., 2020). However, it is beyond the scope of this research to assess each preregistration for quality and rigour. Similarly, adherence to preregistration protocols is another indicator of preregistration value (i.e., if researchers do not strictly adhere to their analysis plan, it may not be useful in reducing QRPs or, in our context, improving statistics attitudes). XX (XX%) of participants in our sample indicated that they did not follow their preregistration plan in their dissertation, which suggests that more research is needed into the implementation of preregistration in a pedagogical context. Practical reasons for this may also be informed by our qualitative data here, which reports perceived (dis)advantages to preregistration. Therefore, future work, depending on our findings, may wish to establish the extent to which preregistration quality impacts on the core outcomes of interest in this work. Future work could also focus on how preregistration may be useful for different types of dissertation, including qualitative studies and analyses of secondary data.

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