Beyond online participant crowdsourcing: The benefits and opportunities of big team addiction science

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Abstract

Participant crowdsourcing platforms (e.g., MTurk, Prolific) offer numerous advantages to addiction science, permitting access to hard-to-reach populations and enhancing the feasibility of complex experimental, longitudinal and intervention studies. Yet these are met with equal concerns about participant non-naivety, motivation, and careless responding, which if not considered can greatly compromise data quality. In this article, we discuss an alternative crowdsourcing avenue that overcomes these issues whilst presenting its own unique advantages – *crowdsourcing researchers* through big team science. First, we review several contemporary efforts within psychology (e.g., ManyLabs, Psychological Science Accelerator) and the benefits these would yield if they were more widely implemented in addiction science. We then outline our own consortium-based approach to empirical dissertations: a grassroots initiative that trains students in reproducible big team addiction science. In doing so, we discuss potential challenges and their remedies, as well as providing resources to help addiction researchers develop these initiatives. Through researcher crowdsourcing, together we can answer fundamental scientific questions about substance use and addiction, build a literature that is representative of a diverse population of researchers and participants, and ultimately achieve our goal of promoting better global health.

Key words: crowdsourcing; addiction science; big team science; researcher consortia; open science

CRediT Statement

CRP: Conceptualization; Project Administration; Writing – original draft; Writing – review and editing. **AJJ:** Writing – review and editing. **LT:** Writing - review and editing. **CDC:** Writing - review and editing. **KSB:** Writing – review and editing.

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Public Significance Statement

This special issue on "crowdsourcing methods in addiction science" focuses on best practices and emerging research that uses online participant recruitment platforms. An alternative method is that of *crowdsourcing researchers* through big team science. In this article, we: (i) review contemporary researcher crowdsourcing efforts and the benefits these would bring to addiction science; (ii) outline our approach to teaching students in reproducible big team addiction science; and (iii) evaluate challenges and their remedies, as well as providing resources, to help others develop these initiatives.

Crowdsourcing broadly refers to the practice of engaging a 'crowd' or group for a common goal to aid innovation, problem solving or efficiency (Framework for Open & Reproducible Research Training [FORRT], 2021). In recent years, crowdsourcing platforms (e.g., MTurk, Prolific, Qualtrics Panels) have been used increasingly in academic research, allowing researchers to capitalise on high-powered sample sizes with comparatively low cost and improve the diversity and representativeness of participants by removing geographic barriers (see Behrend et al., 2011; Stewart et al., 2017 for reviews). In addiction research specifically, participant crowdsourcing has permitted access to populations with specific behavioural and health histories (Fendrich et al., 2021; Strickland & Stoops, 2019; see Ranard et al., 2014 for a review) to enhance the feasibility of complex experimental, longitudinal and intervention studies (Cunningham et al., 2017; Morris et al., 2017; Strickland & Stoops, 2018), as well as qualitative research (Strickland & Victor, 2020). Yet such benefits are often met with equal concerns about participant non-naivety, motivation, and careless responding, which if not considered can greatly compromise data quality (see Jones et al., 2021a).

One alternative crowdsourcing approach, which is often absent from these discussions but has the potential to overcome these issues is *crowdsourcing researchers* through big team science. This involves the large-scale collaboration of researchers and students who work together to solve fundamental scientific questions across different labs, institutions, disciplines, cultures, and continents (Forscher et al., 2020). In this article, we review several contemporary researcher crowdsourcing efforts and the benefits these would yield if they were implemented in addiction science. We then outline our own approach to consortium-based student dissertations; a grassroots initiative that aims to train future scientists in reproducible and transparent big team addiction science. In doing so, we evaluate potential challenges and their remedies and provide a range of resources to instil enthusiasm for more rigorous, diverse, and collaborative scientific endeavours in this field.

Researcher Consortia

In recent years, many scientific disciplines have undergone a ‘credibility revolution’ (also referred to as the ‘reproducibility crisis’, see Baker, 2016; Munafò et al., 2017; Vazire, 2018). Explanations for this range-from ‘dysfunctional’ academic incentives that reward quantity over quality in research outputs (Nosek et al., 2012; Smaldino & McElreath, 2016), the drive for novelty over replication (Makel et al., 2012), an overreliance on underpowered experimental studies (Bakker et al., 2016; Button et al., 2013), and the potential for researcher degrees of freedom to influence the scientific process (John et al., 2012; Simmons et al., 2011). These issues have also begun to be discussed in addiction science (Adewumi et al., 2021; Gorman, 2019; Heirene, 2021; LaPlante, 2019) leading to various ‘open science’ reforms (see Kathawalla et al., 2021; Pennington & Heim, 2021; Pennington et al., 2021). Yet there is one additional explanation that is often overlooked in such discussions – *insufficient resource investment into scientific research* (Cristea & Naudet, 2019; Forscher et al., 2020). In other scientific fields such as physics, it has long been the norm to replicate and reproduce scientific results, often with teams of over 3,000 authors approving a study for publication (Junk & Lyons, 2020), but large-scale collaboration of this kind has been rare in the social sciences and is still notably absent in addiction science. This has led some researchers to call for a ‘CERN for the social sciences’, comprising a distributed network of hundreds of individual laboratories who work in teams to answer global questions (Chartier et al., 2018).

One recent crowdsourcing initiative, led by the Open Science Collaboration (2012, 2014), are the ‘Many Lab’ projects, which aim to estimate the rate and predictors of replication in psychological science. Demonstrating the scale of these efforts, Klein and 50 authors (2014) first tested the replicability of 13 psychological effects across 36 independent samples and 6,344 participants. Soon after came the ‘Reproducibility Project: Psychology’, which brought together 270 authors who attempted to replicate 97 original effects from leading psychology journals (Open Science Collaboration, 2015). As of today, Many Labs have conducted a total of six replication projects, with others investigating variation in replication results across a range of potential study moderators (Ebersole et al., 2016, 2020; Klein et al., 2018, 2019). Enthused by this, many other large-scale collaborations have evolved in developmental (“ManyBabies”, Frank et al., 2020) and educational psychology (“ManyClasses”, Fyfe et al., 2021), animal ecology (“ManyPrimates”, Altschul et al., 2019) and neuroscience (“#EEGManyLabs”, Pavlov et al., 2021). This researcher crowdsourcing technique has also been used to demonstrate how different experimental designs (Landy et al., 2020) and analytical plans (Silberzahn et al., 2018) considerably alter scientific findings. These examples evidence the power of collaboration in driving scientific knowledge forward: by distributing tasks among a large research team, researchers can capitalise on diverse skillsets, increase the efficiency of research resources (such as time and funding), and undertake more rigorous and reliable large-scale studies than is normally achievable.

A similar distributive collaborative network is the Psychological Science Accelerator (PSA; Beshears et al., 2020; Moshontz et al., 2018), which currently includes a network of over 1,200 researchers across 82 countries to facilitate rigorous and generalisable research. Researchers affiliated with the PSA network are guided by five principles — diversity and inclusion, decentralised authority, transparency, rigour, and openness to criticism — which shape the policy and practices underpinning the initiative (see Moshontz et al., 2018). To date, PSA has tested the global generalisability of face perception models across 41 countries and 11 world regions (Jones et al., 2021b), and assessed the effectiveness of behavioural interventions to reduce negative emotions associated with the COVID-19 pandemic (Wang et al., 2021). The PSA therefore enables researchers without external funding to lead studies that would otherwise require large grants and specialised training (Moshontz et al., 2018), and with the involvement of participants and researchers around the world, this crowdsourcing initiative increases the diversity and inclusivity of science beyond narrow demographics (Ghai, 2021; Paris et al., 2020; Rad et al., 2018). Moreover, with the development of initiatives such as StudySwap (Chartier et al., 2018) — an online platform through which researchers post descriptions of projects or resources that are available ("haves") or that they require ("needs") — collaborative networks can be set up easily to maximise resources.

Like others (e.g., Beshears et al., 2020; Forscher et al., 2020; Moshontz et al., 2018; Paris et al., 2020; Uhlmann et al., 2019) we therefore propose that big team science can address many of the problems that scientific disciplines face currently. However, we argue that addiction science is yet to reap the benefits of this crowdsourcing model.

How could researcher crowdsourcing accelerate addiction science?

Many studies in addiction science require access to clinical and/or hard-to-reach populations (e.g., individuals with alcohol dependence; Manning et al., 2021), with the challenges for recruitment carrying the risk of statistically underpowered quantitative studies. Big team science can increase the number of resources for a single study to facilitate sufficiently powered, geographically distributed research (Forscher et al., 2020; Uhlmann et al., 2019). Through initiatives mirroring ManyLabs, PSA and StudySwap, addiction researchers could suggest study proposals and look for interested collaborators to drive this research field forward. This crowdsourcing approach could also further promote citizen science in addiction science by actively involving the general public. For example, through Patient and Participant Involvement (PPI), individuals and organisations can offer additional expertise and ensure that research is conducted in a manner that is sensitive to the needs and preferences of the targeted population (Ferri et al., 2013; Staley et al., 2021). Whilst we acknowledge the long history of community participatory research in addiction science, we share Scheibein et al.'s (2022) view that these individuals should be considered equal investigators in scientific endeavours, which is afforded by big team science.

Researcher crowdsourcing would also aid replication and reproducibility studies within addiction science which, despite repeated calls (e.g., Heirene, 2021; LaPlante, 2019), are undoubtedly lacking in this area. Individual research teams who want to assess whether a given theory, phenomenon or intervention replicates or generalises beyond a single context or population may lack the associated funding, time, and equipment to run such studies. Furthermore, they might find it difficult to translate study materials/measures or know the most appropriate way of modelling the associated data (Beshears et al., 2020). For addiction research in particular, constraints surrounding clinical participant recruitment might mean that it is difficult to re-sample or conduct independent replications and this is particularly relevant when we consider that the statistical approaches required to evaluate the strength of evidence in replication attempts often require very large sample sizes (see Heirene, 2021). But as we have discussed here, big team science has the potential to overcome these issues: by crowdsourcing researchers we can capitalise on resources and skills to create our very own 'ManyLabs' for addiction science. Larger-scale studies would allow us to evaluate whether the literature on which our field stands is replicable and reproducible, that the theories we develop are generalisable across different cultures and contexts, and that the interventions we implement actually make a meaningful impact to people's lives.

Embedding big team addiction science at the grassroots: our approach to student training

The issue of insufficient resource investment within (quantitative) research is magnified for student projects because these are usually undertaken without research funding and under very strict time constraints, whilst at the same time requiring an emphasis on novelty and independence (see Button et al., 2016, 2020). This can result in hundreds of individually supervised projects that may suffer from the same problems seen in the wider literature: small sample sizes combined with questionable research practices can create a factory of false-positive results (Krishna & Peter, 2018; O'Boyle et al., 2017; Olson et al., 2019). If these are then selectively put forward by supervisors for publication, unreliable findings proliferate (Button et al., 2020). Equally, many robust but null findings might never make it out of the file drawer (Heene & Ferguson, 2017; Rosenthal, 1979).

To overcome these issues, in 2016 we developed the 'GW4 Consortium' which brings together students and supervisors from multiple institutions to embark on the undergraduate dissertation process. Since then, we have expanded this approach to include postgraduate training, with the Alcohol Research Consortium (ARC) fostering collaboration between undergraduate and master's students. Working as a larger research team, we devise a scientifically valid study with plausible hypotheses, robust methodology and high statistical power, and an appropriate analysis plan (for examples, see Adams et al., 2021; Tzavella et al., 2021). To ensure individual contributions and adherence to degree accreditation processes (e.g., British Psychological Society, 2019), our students each propose secondary research questions that they would like to investigate, which usually assess individual differences or moderator variables. These students are then trained in reproducible big team science; together we initiate a preregistration plan with all contributors included as co-authors and upload study materials through the centralised Open Science Framework (OSF; www.osf.io). During this stage, students also undertake various tasks, such as drafting ethics applications, creating study materials, and piloting experimental tasks. Importantly, they each contribute to data collection efforts, with each given a target sample size that is then pooled to ensure high-powered designs that can sufficiently answer the research questions. At the end of the project, the students write up their dissertations independently of each other and the lead supervisor prepares the manuscript for publication.

In addition to improving scientific outputs, this approach to the student dissertation offers several unique pedagogical benefits. Through co-production, students not only learn from field-experts but also offer their own insights that improve the research considerably (see also Bangera & Brownell, 2017). Furthermore, this model fosters inclusivity and diversity by including students from a range of academic backgrounds, increasing the accessibility and availability of teaching and research resources across labs, ensuring that contributions are sufficiently acknowledged, and demystifying the "hidden curriculum" around research (e.g., teaching students about the peer review process). This model can be transformative for students who wish to pursue a career in research, but also holds benefits for those who do not. "Open scholarship" of this kind helps students to become consumers of research who are able to evaluate sources critically and understand the importance of transparency (see Chopik et al., 2018; FORRT, 2021). In this way, the integration of teaching with open and reproducible scholarship provides students with the necessary tools to promote long-lasting engagement with science.

Challenges & Remedies

Crowdsourcing researchers is not without its challenges. Here we discuss four of these – incentive structures, infrastructure, social loafing, and research evidence thresholds – and elaborate on strategies to mitigate them (Figure 1).

One of the main problems for big team science is the current academic incentive structures that reward individual contributions and research quantity. This means that any researcher who decides to invest more resources in fewer studies will be 'outperformed' by those who lead several, low-powered studies (Smaldino & McElreath, 2016). Under this same structure, the high administrative burden in organising and coordinating crowdsourcing efforts is not easily creditable on publications and associated career progression and promotion

(Forscher et al., 2020). Solutions to this are based upon variations of contributorship systems for research outputs and their recognition. The first is a consortium-based model to authorship whereby single researcher's names are replaced with a collective entity (e.g., "Open Science Collaboration") and individual researchers are linked via their Open Researcher and Contributor ID (Orcid). A second option, used in the physical sciences, is to list authors alphabetically or randomly to "render the individual contributor subservient to the overarching collaboration" (Birnholtz, 2008, pp. 2). Perhaps the most appropriate method that can encompass the many varied contributions to science, however, is the Contributor Roles Taxonomy system (CRediT; McNutt et al., 2018), which permits authorship to any individual who meets one or more of 14 roles, such as conceptualisation, administration, data curation and writing. Widespread uptake of the CRediT system, which is now used by many journals, would provide a solution to an age-old problem – that individuals who make vital contributions to a research project, such as technicians and research assistants, are rightful authors on research outputs. For an excellent guide on writing manuscripts in large collaborations see Moshontz et al. (2021).

Furthermore, there may be cases where researchers experience barriers to participating in big team science, due to the pressures of their employment contracts and/or funding. Institutions, government, publishers, and funders all control the incentive structures that underpin the research landscape and change therefore requires a coordinated effort from these gatekeepers to attend to and reward excellent team science (Forscher et al., 2020; Frith, 2020; Munafò et al., 2017). This includes changes in hiring, promotion, and progression criteria; for example, the range of evidence used in deciding funding acquisition or career progression could consider evidence of engagement with initiatives that aim to improve reproducibility (Stewart et al., 2021). Similarly, efforts to crowdsource replication studies should be given the same weight in such assessments as novel research studies (see Koole & Lakens, 2012). It is hoped that open science reform will shift incentives so that what is good for the scientist is also good for science (Frith, 2020) and there is growing pressure from the academic community for institutions, government, publishers, and funders to recognise the value of big team science to produce impactful, reproducible, and reliable research (de Jonge et al., 2021; Stewart et al., 2021).

A second related challenge is that of research infrastructure. For big team science to succeed, each researcher and/or institution requires access to the same resources so that science can become more equitable. One of the advantages of researcher crowdsourcing is that it actually opens up resources and funding to those do not have it. However, at the same time we should remain aware that some institutions will have access to certain licensed software and resources, such as that used for videoconferencing or programming, which can create a barrier for others without access to be involved. We recommend the OSF for free-to-use central sharing of preregistration protocols, study materials, data, and code. The freely available Google Suite also has useful resources for collaboration, such as GoogleDocs and GoogleSheets, that allow researchers to work together in real time. Free, open-source software, such as PsychoPy for experiment programming (Peirce et al., 2019), and R (R Core Team, 2021), JASP (JASP Team, 2021) and Jamovi (Jamovi Project, 2021) for data analysis are also invaluable tools for big team science.

Perhaps more of a concern for student crowdsourcing projects is the scope for 'social loafing' or 'free riders' (Latane et al., 1979). This may occur when some team members do not contribute equally to collaborative aspects of the project, such as participant recruitment (Button et al., 2020). The first solution is to initiate a code of conduct which outlines clear expectations of what teamwork entails; consortium members could then agree on responsibilities, tasks, milestones, and credit within initial meetings (Lam, 2015). If a student appears to be falling behind, then supervisors should reach out to understand the reasons and offer pastoral support (Hall & Buzzwell, 2011). Contributions to group work can be tracked directly using the aforementioned collaborative tools (e.g., Google Suite; CRediT) with easy-to-use add-ons that facilitate their usage (e.g., tenzing: Holcombe et al., 2020). Assessment criteria could also include peer evaluations of teamwork and supervisor's assessment of autonomy, with these feeding into the final project grade (see Perron, 2011). Finally, supervisors can promote a culture of collaboration by actively acknowledging examples of teamwork in their mentoring, and signposting where this will be rewarded beyond the dissertation grade. For a detailed discussion of the consortium-based approach see Button et al. (2020), for other related approaches see Wagge et al. (2019), and for a review see Creaven et al. (2021).

As discussed, one of the advantages of multi-lab consortia, particularly for quantitative research, is that larger sample sizes can be recruited. This aids replication by increasing the chance of detecting a true effect (Button et al., 2013; see also Protzko et al., 2021). However, with larger sample sizes, researchers are also more likely to detect trivially small effects, which can render the traditional Null Hypothesis Significance Testing (NHST) framework uninformative (Heirene, 2021; Kaplan et al., 2014). We therefore recommend that, in all quantitative research endeavours, researchers report effect sizes and consider what constitutes a *meaningful* effect in their line of inquiry. This can be achieved through specifying a Smallest Effect Size of Interest (SESOI; for guides see Anvari & Lakens, 2021; Lakens, 2021), as well as considering the theoretical, clinical, or practical importance of effects (see Anvari et al., 2021). In addition, researchers should make use of frequentist equivalence testing or Bayesian analyses to allow for better statistical inferences (see Lakens, 2017, 2018; 2020). Researchers with expertise in this could be asked to collaborate on such projects, further demonstrating the potential for team science to accelerate scientific progress.

Figure 1.

Benefits challenges and remedies associated with big team science.

Big Team Science	
Inputs	**Outputs**
- Collaboration - Resource sharing (equipment, time, funding) - Diverse skills and expertise	- High statistical power - Reliable findings - Diversity and inclusivity - Large-scale replications - Open Scholarship - Citizen science
Challenges	**Remedies**
- Incentive structures - Infrastructure - Social loafing - Evidence thresholds	- New authorship models; changing incentives - Collaborative tools (Google Suite; CRediT; OSF) - Code of conduct/clear communication - Smallest Effect Size of Interest; Equivalence testing; Bayesian analyses

Conclusions

We argue that addiction science is yet to adopt and therefore gain the substantial benefits of big team science. Large-scale researcher crowdsourcing offers this field a way to "scale-up" on resources to conduct robust, replicable, and reproducible research, recruit from representative and/or hard-to-reach populations and promote inclusivity and diversity. This can be achieved through researcher-led initiatives, taking inspiration from ManyLabs, PSA and StudySwap, and/or student-centred initiatives, such as the consortium approach to student research training. If the unique challenges of big team science are recognised, this method of collaboration can greatly improve the efficiency and value of addiction science: together we can answer fundamental scientific questions about substance use and addiction, build a literature that is representative of a diverse population of researchers and participants, and ultimately achieve our goal of promoting better global health.

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