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'One size doesn't fit all': Lessons from interaction analysis on tailoring Open Science practices to qualitative research

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Abstract

The Open Science Movement aims to enhance the soundness, transparency, and accessibility of scientific research, and at the same time increase public trust in science. Currently, Open Science practices are mainly presented as solutions to the 'reproducibility crisis' in hypothetico-deductive quantitative research. Increasing interest has been shown towards exploring how these practices can be adopted by qualitative researchers. In reviewing this emerging body of work, we conclude that the issue of diversity within qualitative research has not been adequately addressed. Furthermore, we find that many of these endeavours start with existing solutions for which they are trying to find matching problems to be solved. We contrast this approach with a natural incorporation of Open Science practices within interaction analysis and its constituent research traditions: conversation analysis, discursive psychology, ethnomethodology, and membership categorisation analysis. Zooming in on the development of conversation analysis starting in the 1960s, we highlight how practices for opening up and sharing data and analytic thinking have been embedded into its methodology. On the basis of this presentation, we propose a series of lessons learned for adopting Open Science practices in qualitative research.

INTRODUCTION

Trusting the outcomes of scientific research is a fundamental prerequisite for scientific progress. In the last few decades, the credibility of scientists and their findings has waned due to prominent cases of fraud, such as that of the social psychologist Diederik Stapel, who published over 50 articles using invented data (Levelt Committee et al., 2012), and due to the failure to replicate well-known effects, like 'ego-depletion' (Hagger et al., 2016). In response, the scientific community, with psychology at the forefront, has started to promote practices that increase the transparency and accountability of research processes. Widely known as Open Science (OS), these practices preponderantly address issues germane to hypothetico-deductive methodologies associated mainly with quantitative research. While there have been some attempts to adapt OS to qualitative methodologies, its uptake by qualitative researchers, including social psychologists, seems to be lagging behind.

In the first part of this article, we will argue that the ostensibly moderate adoption of OS by qualitative social psychologists is partially the result of an insufficient fit between the OS practices that are currently being promoted and qualitative methodologies. We will attempt to demonstrate that, in its current form, OS is mainly geared towards solving problems inherent to quantitative research. While attempts have been made to adapt OS practices to qualitative methodologies, we argue that this approach is suboptimal because OS practices can often not be satisfactorily adjusted to address issues within qualitative social psychological research.

In the second part of the article, an alternative course of action is proposed: instead of adapting mainstream OS practices, qualitative researchers could develop tailored procedures uniquely equipped to deal with the challenges they are facing. To illustrate this organic development of OS practices, we will present the case of Interaction Analysis (IA), a set of approaches comprising discursive psychology, conversation analysis, ethnomethodology, and membership categorization analysis that have been employed in qualitative social psychological research for over 35 years (e.g. Antaki, 1988; Billig, 1987; Edwards & Mercer, 1987; Potter & Wetherell, 1987). These approaches already include OS principles and procedures that are embedded in their methodology and that are designed to address anticipated limitations associated with interaction analytic research. Thus, we advance the argument that interaction analysts are already practising OS in forms that are not yet on the OS radar. The article concludes with a series of 'lessons learned' from IA for expanding OS practices in social psychological research.

BRIEF OVERVIEW OF THE OPEN SCIENCE MOVEMENT

'Open Science' (also 'Open Research/Scholarship') refers to a set of practices aimed at enhancing the transparency, efficiency and accessibility of scientific research processes and products, with the aim of building public trust in scientists and scientific findings (cf. Vicente-Saez & Martinez-Fuentes, 2018; see also the editorial of this special section). While Open Science practices have been advocated for by sociologists of science for over 40 years (e.g. Merton, 1979), the Open Science Movement (OSM) developed momentum in psychology after a series of large-scale replication projects failed to reproduce many of the significant results reported in a number of experimental and correlational studies published in prominent scientific journals (Camerer et al., 2018; Open Science Collaboration, 2015). This set the OSM on a path towards identifying and remedying issues that can threaten the trustworthiness and robustness of experimental and correlational research and

their findings. In a prominent manifesto for Open Science, Munafò et al. (2017) identified a range of problematic practices, such as failing to control for researcher or publication biases, designing low-quality studies that are underpowered or lacking sufficient control, and scouring datasets in search for statistically significant results. Similar endeavours followed in other fields such as communication studies (Dienlin et al., 2021), clinical psychology (Tackett et al., 2019) and neuroimaging (Gorgolewski & Poldrack, 2016). Through these undertakings, the OSM has been configured not by design, but fortuitously to deal with deficiencies that threaten the credibility of hypothetico-deductive experimental and correlational research leading to the wide use of the labels 'reproducibility crisis' or 'replicability crisis' to refer to the range of problems that OS practices can address. Thus, the vocabulary of quantitative research methodology, which often relies on positivist epistemological assumptions, has ended up dominating the discourse of the OSM (Nelson et al., 2021) and now sets the agenda for its advancement. As we will argue in the next section, these assumptions often render Open Science practices, that are predicated on them, difficult to reconcile with qualitative methodologies.

OPEN SCIENCE AND QUALITATIVE METHODOLOGIES

Qualitative methodologies are often described in comparison to or in opposition with quantitative methodologies as approaches that rely on the examination of words instead of numbers (Braun & Clarke, 2013; Silverman, 2011). However, upon reflection, it becomes clear that even this minimal criterion fails to adequately distinguish between the two orientations as, for example, many questionnaires employ textual labels to accompany numerical scales (cf., Silverman, 2011) and many experimental studies rely on insights generated through qualitative methods, such as debriefing interviews, to make sense of quantitative findings (Stainton Rogers, 2011).

Qualitative approaches are enormously diverse. For example, what we understand by 'words' as data varies from, for example short responses provided by participants to interviewers' questions, to lengthy naturally occurring conversations that participants conducted independent of the researcher's intervention. Moreover, qualitative methodologies differ with respect to what they 'do' with their data (Madill et al., 2000); that is, the methods employed to analyse, interpret, or otherwise make sense of researcher observations or participants' accounts and the inferences drawn about the 'world beyond the words'. Finally, qualitative research methods differ immensely in terms of their ontological and epistemological assumptions. In fact, some methods are so radically different in their treatment of language and the knowledge derived from studying it, that they do not fit within either the qualitative or the quantitative 'box' (Stokoe, 2020). In their editorial on *Innovating qualitative research methods*, LaMarre and Chamberlain (2022) go one step further and argue that the heterogeneity of qualitative research methodologies is under threat from an impetus for standardization, for example through the introduction of journal article reporting standards for qualitative research (Levitt et al., 2018). Echoing Clarke (2021), the authors highlight that this trend can benefit mainstream qualitative approaches while leaving behind non-traditional ones. Consequently, social psychologists who employ non-traditional methods, may need to do additional work to explain and legitimize their approaches and find ways to represent their research in line with standards that might not be entirely applicable to them (see also the discussion on qualitative preregistration below). As a consequence, social psychologists could be demotivated to choose less conventional methods over established ones, leading to a qualitative research landscape dominated by interview-based research (LaMarre & Chamberlain, 2022).

To sum up, despite the acknowledgement that the distinction between quantitative and qualitative methodologies is unhelpful and not straightforward (Silverman, 2017), it continues to be used within social and behavioural sciences, including in discussions of OS (e.g. Dienlin et al., 2021; Tamminen & Poucher, 2018; Sukumar & Metoyer, 2019). The attempts to incorporate OS within qualitative methodologies, which we review below, are thus complicated by being defined in terms

which are not always directly applicable and that obscure or stifle the diversity within qualitative methodologies.

Adoption of Open Science by qualitative researchers

To date, qualitative methodologies have occupied a peripheral position in the OSM. Unlike quantitative research that has come under fire across a range of disciplines from medical to social sciences for an ostensible decrease in the trustworthiness of scientific results (Ritchie, 2020), the dependability of qualitative research has not been called into question yet. However, calls for qualitative researchers to adopt OS practices have been issued (Anczyk et al., 2019; Karhulahti, 2022; Sukumar & Metoyer, 2019). In what follows, we review existing developments to implement replications, preregistration and data sharing practices within qualitative methodologies.

Reproducibility and replicability of qualitative research

To the best of our knowledge, there have not been any attempts at conducting systematic checks of the reproducibility of findings from qualitative research, or at setting up large-scale replications like the Reproducibility Project (Open Science Collaboration, 2012). Admittedly, these are not core issues associated with the methodological integrity of qualitative research (Levitt et al., 2018), especially since not all epistemologies advance the same understanding of reproducibility or even aim to yield reproducible findings (Tamminen & Poucher, 2018). A core feature of some qualitative techniques, such as autoethnographies, recognize that analysts have a central role in the research process and generate their own memories and understandings of what they have seen, heard and felt (Hammersley, 2010), thus their unique world view cannot be bracketed or replicated as such. Instead, researchers are encouraged to practise transparency and reflexivity and bring to the forefront how their life experiences, values, and membership in various identity categories shape their interpretation of the data.

Still, others hold the view that replications, if redefined to be inclusive of qualitative methodologies, can help to articulate and compare researcher biases, act as an alternative to transferring findings between similar contexts, and compare research methods amongst other benefits (see Sukumar & Metoyer, 2019). For example, Sukumar and Metoyer (2019) claim that some methods within approaches such as phenomenology, sociolinguistics and critical genres would be amenable to replications. The authors also put forward a new definition of replications which highlights that they need to be conducted not by the original research team, but by an independent group. The latter would duplicate one or more aspects of the original study to conduct an interpretative comparison of the original and the replication. While this extended understanding of replication seems appealing, it does not yet encompass all qualitative approaches and it might give the false impression that the methodological integrity of qualitative research is at stake. It remains to be seen whether researchers accept the challenge of trying to replicate qualitative findings in accord with the above suggestions, but our sense is that, even in its redefined form, replication rarely addresses genuine concerns inherent to most qualitative methodologies.

Preregistering qualitative studies

One area of OS where qualitative researchers have made strides is preregistration. Initially, the idea of preregistering qualitative projects was called into question on account that qualitative studies neither benefit from, nor are amenable to having their design laid out in advance (Haven & Van Grootel, 2019). These misgivings have been judiciously dispelled (Haven & Van Grootel, 2019) and to date there are several preregistration and pre-analysis templates available for qualitative research (e.g. Haven & Van

Grootel, 2019; Piñeiro & Rosenblatt, 2018). The form designed by Haven et al. (2020) incorporates the views of researchers representing several different qualitative traditions and, thus, is supposed to be fitted to a wide range of qualitative approaches. However, as we show below, even this carefully thought-out template still falls short of properly accommodating all qualitative research methods.

Despite the effort to be inclusive and flexible, a glance at the template reveals that the choice in terminology accommodates some qualitative approaches, but not others. Many sections of the form include response alternatives listed from amongst established qualitative research methods with an additional 'Other' option that allows researchers, whose approach is not pre-listed, to include it in the template. However, this format ends up 'othering' less established qualitative methods and reinforcing the status of mainstream ones. Furthermore, for some sections, this option is missing and researchers are required to fit their research design into pre-established linguistic categories, which might end up mischaracterizing their study.

For example, in Section 13, researchers need to specify the study's 'sample size', meaning the number of 'interviews/observations/focus groups' that will be conducted. This item poses several difficulties. First, not all qualitative approaches postulate a representational relationship between the data and the social world which produced them. Second, for some approaches, like conversation analysis, what constitutes a sample item is not clear. Conversation analysts collect and examine instances of naturally occurring social interactions to identify patterns and regularities therein. To build such collections, which can range from a few to hundreds of cases, conversation analysts often record tens or hundreds of interactions from one or more settings, amounting to up to hundreds of hours of data. Furthermore, a collection comprises diverse cases, including core, boundary, and deviant cases (Hoey & Kendrick, 2018) and the size of a collection fluctuates throughout the analysis process. Simply reporting a total case count obscures the diversity within a collection, since samples are supposedly composed of homogenous entities. So, which of these numbers – the number of interactions, the total hours of data, or the number of cases included in the collection at a particular point in time – is equivalent to the 'sample size'? Probably none of these, especially since conversation analysis does not rely on quantification to validate analytic findings. It is not the frequency with which a particular practice recurs within the data, but its demonstrable patterned organization that constitutes the proof for its validity (Clayman & Gill, 2004).

To conclude, we hope to have illustrated that the language used in one of the most popular preregistration templates, developed specifically for qualitative methodologies falls short of accommodating some approaches, and may force researchers to misrepresent their studies or give up on preregistering them. Thus, the template ends up favouring established methods. Over time, this can create inequalities in the level of engagement with preregistration and other OS practices across qualitative approaches. Let us emphasize: we are not arguing that preregistering a qualitative study cannot or should not be done, just that, in the case of qualitative preregistration, 'one size fits all' may not be a felicitous solution.

Sharing qualitative data

An area of debate at the interface of the OSM and qualitative methodologies is the sharing and reusing data. The principles of reusing data align with the OSM (enhancing transparency and efficiency and accessibility of scientific processes and products) and are widely supported by participants (Mozersky, Parsons, et al., 2020), yet there is resistance to openly sharing all qualitative data on epistemological and ethical grounds (see Joyce et al., 2022, for a review of those grounds). The key arguments for a more nuanced handling of sharing data within the OSM pertain to: (1) ensuring participant anonymity, especially when qualitative data can be particularly intimate and fully informed consent about the (possibly limitless) data reuse can be difficult to communicate to participants (Branney et al., 2019); (2) possible errors and inconsistencies in datasets which might have significant consequences, such as a lack of public trust in the scientific enterprise, or a tragic loss of life (Brown et al., 2018). On epistemological

grounds, objections have been raised on the basis of (3) qualitative data being usually highly contextual (in both reflecting the researchers' beliefs, judgements, disciplinary assumptions and the environment/ time the data were collected) which can make it difficult or impossible to be meaningfully reinterpreted by another researcher (Branney et al., 2019; Hammersley, 2010).

The complexity of (re)using qualitative data (e.g. visual, interview, observations) does not simply mandate a reflexive paradigm to the research, but warrants a rethink of whether and how such data can ever be reused in secondary analyses. Moreover, the very distinction between primary and secondary qualitative analyses has come under increased scrutiny (Joyce et al., 2022). Clearly these concerns, while not unique to qualitative data, cannot be solved via a narrow one-size-fits-all approach (cf. Joyce et al., 2022) which does not necessarily account for the breadth of qualitative approaches and data.

We started this section by highlighting the diversity of approaches within qualitative social psychological research and went on to illustrate how some of the practices that are currently being employed to enhance the transparency and trustworthiness of quantitative research are either insufficiently adaptable or fall short of addressing issues germane to qualitative methodologies. In what follows, we introduce an alternative approach to the implementation of OS within qualitative social psychological research: the organic development, within IA, of OS practices that specifically address vulnerabilities intrinsic to this qualitative approach.

INTERACTION ANALYSIS AND OPEN SCIENCE

Interaction analysis incorporates discursive psychology, conversation analysis, ethnomethodology, and membership categorization analysis, four highly compatible research traditions, employed across the social sciences, with discursive psychology having been developed within psychology. We refer to IA not as a unique approach, but an umbrella term to describe the four research traditions. While IA utilizes qualitative data, it does not fit neatly into either the qualitative or the quantitative 'box' (Stokoe, 2020). Specifically, interaction analysts work almost exclusively with recordings of naturally occurring social interactions (Potter & Shaw, 2018), though conversation analysis can be combined with experimental and statistical methods (de Ruiter & Albert, 2017). Analysts refrain from inferring what participants are thinking, feeling or experiencing based on what they say or do (Humă, Alexander, et al., 2020). Instead, IA is designed to excavate the actions accomplished by participants through linguistic, embodied and material resources.

Interaction analysis takes an inductive approach to examining human social interaction and theorizing its organizing principles. IA differs from other qualitative approaches by promoting 'unmotivated looking', meaning that researchers leave aside any preconceptions about what they expect or want to find and instead explore the data with an open mind (Psathas, 1990). Even once a research question has been formulated, it can still be further adapted as the research progresses. To a scientist trained in hypothetico-deductive research, this practice looks suspiciously similar to HARKing (Albert & de Ruiter, 2017). But far from jeopardizing the methodological integrity of a study, this practice ensures the mutual adequacy between data and research aims (Humă, Alexander, et al., 2020).

Interaction Analysis is also compatible with a more directed 'motivated looking' approach, whereby researchers collect and examine either data from certain environments such as sales encounters (Humă, Stokoe, & Sikveland, 2020) or family meal-times (Potter & Hepburn, 2020), or data featuring specific social phenomena such as emotion (Weatherall & Stubbe, 2015) or racism (Burke & Demasi, 2020). Still these focal interests are unencumbered by theoretical notions or hypotheses in search of support, thus allowing interaction analysis to be data-driven and to foster unexpected observations.

Another defining feature of interaction analysis consists in its almost exclusive reliance on the examination of recordings of naturally occurring social interactions such as calls to helplines, disputes on public transport, political debates, medical consultations, family meals, to name only a few. These encounters are subject to Hepburn and Potter's (2021) two tests for naturalistic data: (1) the encounter should have taken place even without the involvement of the researcher and (2) the data should allow

analysts to retrieve the original actions performed by the participants. Using this kind of data, discursive psychologists have documented, for example how emotions such as crying are interactionally managed (Hepburn & Potter, 2007), how derisive laughter can serve an argumentative purpose (Demasi & Tileagă, 2020), and how displaying empathy can contribute to the achievement of specific institutional outcomes (Ford et al., 2019).

Importantly, IA distinguishes itself from most qualitative approaches that rely on interpretative or constructionist epistemologies in which the researcher plays an active role in making sense of participants' accounts and co-produces the data and meaning therein. Instead, IA adopts a members' perspective and relies on the analyses and orientations that individuals display in and through their talk-in-interaction through such practices as the next turn proof procedure (Edwards, 2004), or self-repair (Drew et al., 2013). Interaction analysts refrain from speculating about what people think, feel, know, or understand and instead rely on what is demonstrable in the data and, thus, accessible to any natural language user (Jacobs, 1988). All interaction analytic observations need to be rigorously accounted for, checked, and checkable in the analysis (see Schegloff, 1996).

Interaction Analysis encompasses four compatible research traditions. Conversation analysis, initiated by Harvey Sacks (1992), focuses on two basic components of interaction (Clift, 2015): *action*, which is what we do with the words we use (see Austin, 1962), for example making a complaint, telling a story, apologizing, requesting and, *sequence*, which is the chronology and structure of how actions are performed in and through talk and embodied conduct. Membership categorization analysis, developed by Hester and Eglin (1997) based on their understanding of Sacks' writings and lectures (Sacks, 1992), explores the organization of categories and associated inferences. The third tradition, discursive psychology, is interested in how individuals manage psychological topics such as attitudes, memory, identity, or social influence in and as part of their daily lives (Edwards & Potter, 1992). Finally, ethnomethodology, introduced by Harold Garfinkel (1967), excavates the methods individuals use to organize everyday interactions and to make sense of their own and their interlocutors' conduct. Despite their specific foci, these four approaches share an analytic outlook that does not, generally speaking, entertain acontextual explanations of the phenomenon unless locally and demonstrably expressed.

Opening the methodological 'black box'

Conversation analysts' preoccupation with the rigour and transparency of their analytic enterprise transpires from across early conversation analytic work (e.g. Sacks, 1984, 1992; Sacks et al., 1974). In the lectures delivered by Harvey Sacks between 1964 and 1972 and collected by Gail Jefferson in the two-volume *Lectures on Conversation* (Sacks, 1992), two distinct, but interrelated aspects of reproducibility transpire (Schegloff, 1992): the reproducibility (i.e., duplication) of research findings and the reproducibility of the analytic endeavour. To address both aspects of reproducibility, conversation analysts have developed several methodological procedures, which we outline below, and these are now widely employed in interaction analytic research.

All interaction analytic empirical publications include extensive data extracts enabling readers to independently check all analytic claims. This is achieved by incorporating detailed transcripts within the papers' analytic sections. Most transcripts are produced according to the conventions for transcribing talk-in-interaction originally developed by Gail Jefferson (2004). Increasingly, for transcribing video data, the conventions introduced by Lorenza Mondada (2018) have been adopted. These transcription systems ensure that the key features of speech – such as intonation, pitch, silences and overlaps – and of embodied conduct – such as the start, trajectory, and end of body movement – are accurately represented in the data extracts (Hepburn & Bolden, 2017). This practice not only allows authors to refer to these details in their analyses to support their claims, but it also enables readers to verify these claims independently. Furthermore, readers get access not only to what the authors chose to focus on in their analyses, but to all other transcribed features of the scrutinized interaction, which allows them to entertain alternative analyses of the data.

Interaction Analysis's preoccupation with rigour results in IA researchers mostly abstaining from making analytic claims that are not backed up by evidence from the transcripts. This means not only refraining from referring to events that are not included in the shown data, but also from explaining participants' actions in terms of their psychologies (i.e., wants, needs, thoughts, emotions) or their social identities (e.g. woman, doctor, child, husband), unless the latter have been made relevant and consequential by the participants themselves (Schegloff, 2007). Instead, analysts rely on prior empirical findings from published research to corroborate their observations.

In fact, since its inception, IA, and especially conversation analysis, has accumulated a large body of coherent empirical results, much like what Kuhn (1962) would call 'normal science'. Importantly, by drawing on, checking and validating prior results in new datasets, IA allows for the 'integrative replication' (Freese & Peterson, 2017, p. 151) of these findings. This constitutes an informal replication process, the by-product of researchers' efforts to produce new knowledge by building on existing empirical findings (Freese & Peterson, 2017).

In addition to the above-described tools providing for 'reproducible descriptions' (Sacks, 1992, p. 11) of social phenomena and for the integrative replication of findings, IA also employs practices for enhancing the intersubjective verifiability of analytic claims, prior to write-up. This is achieved via data sessions, wherein researchers show their data prior to publication, and in some cases, prior to having any findings. These sessions offer a fertile ground for jointly interrogating data, for corroborating discoveries, for learning the method, and for retelling lay observations in a refined and precise manner. The session follows a regular structure (see ten Have, 2007 for an extended description of the structure), though the specifics might differ between research groups. The joint interrogation of data adds a layer of rigour to the analytic process through the intersubjective substantiation of analyses.

Opening-up qualitative data

A tenet of the OSM, open data, is a principal way that scientific transparency can be achieved. Threats to scientific trustworthiness stem from findings based on inaccessible data, for which it is not clear what evidence has been used to arrive at the findings and so the reader (and public at large) must rely on the word of the author. For interaction analysis, the transparent use of data is a staple of the method and a consequence of the early scholars using what data they had available to them and sharing them amongst the small community. Transparent use and reuse of data is aptly surmised by Sacks (1984, p. 27): 'People often ask me why I choose the particular data I choose. [..] And I am insistent that I just happened to have it, it became fascinating, and I spent some time at it'.

Methodologically and historically, IA has preserved features which have made it well-suited to ensure open data (Albert et al., 2018). Data are often shared prior to, in publications and following project completion. It is expected that IA publications will feature detailed transcriptions using appropriate conventions. This not only allows findings to be independently verified by reviewers and readers, and but it also enables scholars to reuse the data in their own analyses of the same or of different phenomena. Technological advances and the ability to embed recordings in journal publications[1] is beginning to raise those expectations, for example, IA articles that examine 'online' recordings (e.g. YouTube, TikTok) have started to include links to original videos (e.g. Joyce et al., 2021). Increasing data accessibility is an effort to formalize the central yet capricious practice of IA researchers retaining and sharing the original recordings. Open data is thus not only a practical requirement for publication, but a guiding principle through which incremental steps are taken to continually improve data accessibility.

Sharing one's data and analysis is fundamental for IA and practising OS. This goes hand-in-hand with documenting the research process and making it available for others to see (Tamminen &

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[1]See for example the journal *Social Interaction* at https://tidsskrift.dk/socialinteraction

Poucher, 2018). IA does not typically use the terms 'reproducibility' and 'replicability' as they imply that efforts to ensure transparency and fit with the OSM are exogenous to the science, but for IA these are baked into its methodology.

CHALLENGES FOR THE OPEN SCIENCE AGENDA OF INTERACTION ANALYSIS

Highlighting how IA might usefully contribute to the discussion on OSM and qualitative methodologies has hopefully demonstrated that one size does not fit all when it comes to practising OS. In the remainder of this article, we critically reflect on the challenges that interaction analysts, and to some extent qualitative approaches at large, must still tackle to advance the OS agenda.

Expertise, technology and access

IA's development, focus, and engagement in OS practices has been shaped by the available technology of the time. For example, CA began with the wider availability of consumer recording technologies allowing researchers to replay, pause, and slow down recordings of social interaction, thus permitting a very fine-grained approach to analysis. Importantly, recordings and transcripts were available to be duplicated and physically shared which formed one of the key pillars of IA – the impetus on sharing data. The early practices for sharing data are not without criticism, which we discuss later in this section. Over time, the development and availability of technology has allowed for materials to be securely stored and widely shared in online repositories – for example, the personal website of conversation analyst Emanuel Schegloff[2] or the CABank[3] at first, and then more recently the Open Science Framework, and ResearchGate.

Expertise

The promise of these new and accessible systems has been huge, yet fulfilling that promise has required adoption and investment by institutions and individuals. The UK Research and Innovation (UKRI) released a concordat in 2016 stating that all publicly funded research data must be openly available and, in a recent review, reemphasized that there should be as few restrictions as possible on data (UKRI, 2016). Despite this, concerns persist about the secure sharing of data, the expertise needed to choose an appropriate platform, and the use of those platforms (Mozersky, Walsh, et al., 2020), especially considering data protection regulations in the United Kingdom and the European Union. For IA (and other qualitative approaches), concerns about safeguarding data are often exacerbated by ethics committees which impose restrictions to data collection and sharing rendering any (re)use or checking of data difficult if not impossible. To be clear, we are not arguing against safeguarding participants, but highlighting that a lack of relevant expertise in unfamiliar disciplines and technologies – for both ethic committees and for researchers – may inadvertently erect barriers to fully openly accessible data. So while funders and the OSM push for open research data, the perception that IA (and qualitative) data are incredibly sensitive and confidential means that for many studies data sharing becomes virtually impossible due to ethical restrictions.

While qualitative researchers can formulate arguments to counter misconceptions and advocate against overly restrictive or burdensome barriers, it is much more difficult to solve the problem of

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[2]https://www.sscnet.ucla.edu/soc/faculty/schegloff/

[3]https://ca.talkbank.org/

data splintering. In IA, as the field and technology have developed, new tools, transcription systems and software have been created. This has had undoubted benefits for research, but the hidden barrier of expertise especially in the face of the OSM are yet to be addressed. Those barriers may include, for example additional training, software and time, all of which disproportionately impact early career researchers particularly interdisciplinary qualitative early career researchers, which might rely on diverse and varied datasets. Accessibly preparing data is a remedy, but not a panacea, and instead shifts the burden to the data sharer. Further critical discussion on where the burden of data preparation lies is needed (but see Pownall et al., 2021 on the costs of OS practices for early career researchers).

Technology

It is not only a lack of relevant expertise which impedes IA's engagement in the OSM but also technology. While IA has been quick to adapt new technologies for data collection and analysis, other areas have lagged behind. Many traditional outlets such as academic journals are ill-equipped to host multimedia materials, so although IA typically presents data alongside the analysis, this usually includes anonymized transcripts and not audio or video recordings. Consequently, the relationship between the discipline-specific practices and solutions, and the available infrastructure can both help and hinder engagement with the OS. For instance, constraints on word count and formatting in journals might result in a limited description of the steps taken to arrive at the analytic findings, which, in the interest of transparency for readers outside of the discipline, can pose a challenge to understand the processes through how the researcher arrived at those findings.

These problems relating to infrastructure impact the consistency in presentation of data. With only the ability to present data as textual representations, the reviewer and reader must trust, without the ability to check, that those representations accurately reflect the recordings. The problem of consistency and verification pervades the storing and sharing of data in IA. Albert and Hofstetter (in prep. a) describe this issue and suggest some common practices for managing data – such as, how to catalogue and label data, and what tools exist to analyse large corpora. We agree with their argument that 'any prescriptive technological recommendations would quickly become redundant' (para 1), so rather than give exact solutions and prescribe concrete guides to data management, we would suggest that, in the interest of data reuse and ensuring participant confidentiality, that data corpora be consistently, accurately, and fully described with protocols narrating the technical choices made in the process of data storage.

Access to data

Interaction Analysis can be incredibly time-intensive and, coupled with research in harder-to-access environments, it can prove out of reach for early career and marginalized researchers who are restricted by time and precarious employment. It is a well-made argument that access to datasets benefits both these groups (see Jepson et al., 2017) and participants and institutions that may be burdened by the investment necessary to engage in research. Transparency and access by way of the OSM eases the time and cost burden on researchers for gaining access, collecting, and transcribing/preparing data. Simply put, widening access to data is one way that a research community can support the work of early career and marginalized scholars and foster an environment where data are continually scrutinized to check and expand upon prior work.

The black box of IA data has traditionally been opened following project completion with data corpora stored in physical and online repositories, mirroring the practices of other disciplines. However, the difficulty of relying on this as the sole method of ensuring open data is that corpora are often sporadically organized and inconsistently labelled (Albert & Hofstetter, in prep. a), hindering the efficiency

and reusability of purportedly open data. One such example of the pitfalls of data access has recently been reflected on within the conversation analytic community in relation to its handling of its 'classic data' corpus. For conversation analysis, 'classic data' refers to data corpora central to the early work in the field and which have been widely reused and reanalysed in the course of the field's development. The problem lies in issues of openness and representation. For openness, despite there being alleged unrestrained access across the conversation analytic community, the reality is that due to ethical concerns, only a small subset of scholars has access to the corpus. This is an issue which is reviewed in detail by Albert and Hofstetter (in prep. b), who explore the problem of this creating an in- and out-group sense within the community. Moreover, these data collected in a particularly middle-class area on the west coast of the United States in the 1960s and 1970s have favoured a particular view of language use which has pervaded the history of conversation analysis. Recent efforts by groups such as the Ethnomethodology and Conversation Analysis for Racial Justice (EMCA4RJ) have sought to address the lack of diversity in data by supporting the access to data in different languages and from traditionally minoritized communities in IA (Sciubba et al., 2021).

Data accessibility, whilst the gold standard for transparency still presents problems when improperly handled. To be clear, we are arguing that data access in IA has afforded rich opportunities for subsequent analyses and has furnished IA with reproducibility and replicability baked into the process. However, ad-hoc sharing practices controlled by a small group in the community and an over reliance on a limited datasets can adversely impact the OSM efforts.

LESSONS LEARNED

Open Science unquestionably benefits psychology. To date, it has gone some way to redeem the credibility of psychological research in the wake of the far-reaching 'reproducibility crisis'. This article has shown that, as it stands, the OS agenda has been mainly centred around challenges faced by quantitative research. We argued that current efforts to include qualitative research in the OSM by adjusting OS practices to fit with qualitative methodologies fall somewhat short of their goal. Specifically, these attempts do not properly address the heterogeneity of qualitative methodologies and do not provide solutions to their unique challenges. We contrasted this 'one size fits all' approach with the organic incorporation of OS practices within interaction analysis. In this last section, we put forward three lessons that can be learned from how interaction analysts developed OS practices that mitigate the challenges inherent to this methodology.

Lesson 1: 'Look inward'

Interaction analysis has developed procedures to deal with issues related to reproducibility, transparency, and data sharing that were identified as threatening the integrity of the method. The transparent use and reuse of data in IA is grounded in the early development of the approach because the researchers 'happened to have it' (Sacks, 1984, p. 27) and so other researchers could 'make of it what they could' (p. 26). The way that IA approaches examine and handle their data – by not entertaining acontextual explanations of phenomena unless that context is demonstrably made relevant in the interaction, and by sharing data during and after the analysis – underscores the principles of verification and transparency. Even if this may be unique to IA, other qualitative approaches may have developed similar safeguarding procedures that are compatible with their epistemological assumptions. The emphasis on data accessibility throughout the research process has benefitted not only the individual researchers via the support for arriving at and verifying their findings, but also the wider academic community via opportunities for integrative replication and reproducibility. It is worth acknowledging these practices and relating them to the OS agenda.

Lesson 2: 'Look outward'

Interaction Analysis's distinct epistemology has influenced the natural incorporation of Open Science practices by its practitioners, and whilst many of these are unique to the approach, they still might usefully inform or be adopted by other methods to enhance their transparency and trustworthiness. One such example is given by Albert and de Ruiter (2017) who advocate for legal HARKing which experimental psychologists with an interest in studying social encounters could adopt. This means that before designing an experiment, the researchers may want to consider examining some naturally occurring data to ground their theorizing and hypothesizing in real life examples. The lesson here is that qualitative methodologies can also offer practical solutions to credibility challenges faced by quantitative research, not only the other way around.

Lesson 3: 'Look ahead'

While there are a number of Open Science practices used amongst qualitative approaches barriers still exist in a few areas. For instance, technology and knowledge lag behind the willingness of qualitative researchers to engage in Open Science. New technologies have proven to be immensely beneficial for verifying findings, making data accessible, and promoting trust in the scientific process. Whilst new technologies have arrived to provide solutions, the resources required to learn and adapt to these systems present barriers to the fullest engagement with Open Science. As we discussed throughout this paper, many of the barriers to Open Science are solved with tools and concepts designed for quantitative research which leaves qualitative researchers to figure out what problems might be solved by these solutions rather than the other way around. Thus expertise, from funders to ethic committees to repository administrators, is necessary to avoid imposing ill-fitted solutions for Open Science barriers which do not exist for qualitative research and vice versa, for finding solutions to barriers unique to it.

Taken together, these three lessons hopefully demonstrate the potential of qualitative social psychological researchers not only to embrace, but also to drive innovation within OS. While it may appear at times that qualitative methodologies are incompatible with OS, we have aimed to highlight that these are cases of specific qualitative approaches being at odds with specific OS practices, but not with underlying OS principles. Finally, we have shown that some qualitative social psychologists – those who have been using interaction analytic methods – have already been practicing OS for several decades. We hope this will inspire social psychologists working with other methodological approaches to identify OS practices within their own field.

CONFLICT OF INTEREST
All authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT
Data sharing is not applicable to this article as no datasets were generated or analysed during the current study.

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