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Article

DARE to be different? A novel approach for analysing diversity in collaborative research projects

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Abstract

Growth in collaborative research raises difficulties for those tasked with research evaluation, particularly in situations where outcomes are slow to emerge. This article presents the 'Diversity Approach to Research Evaluation' (DARE) as a novel way to assess how researchers engaged in knowledge creation and application work together as teams. DARE provides two important insights: first, it reveals the differences in background and experience between individual team members that can make research collaboration both valuable and challenging; second, DARE provides early insights into how team members are working together. DARE achieves these insights by analysing team diversity and cohesiveness in five dimensions, building on Boschma's multi-dimensional concept of proximity. The method we propose combines narratives, maps, and indicators to facilitate the study of research collaboration. The article introduces the DARE method and pilots an initial operationalization through the study of two grant-funded biomedical research projects led by researchers in the UK. Suggestions for further development of the approach are discussed.

Key words: collaborative research; team science; diversity; biomedical research; network mapping; quantitative–qualitative analysis.

1. Introduction

This article presents a novel approach for the assessment of how teams of diverse individuals collaborate during knowledge production and application. The Diversity Approach to Research Evaluation (DARE) generates insights into collaborative processes using a combination of narratives, maps, and indicators. The method operationalizes a previously elaborated conceptual framework that defines the different kinds of diversity which need to be bridged during knowledge intensive collaborations (Molas-Gallart et al. 2016). The approach enables the study of the diversity of teams engaged in collaborations and reveals how such diversities are bridged through collaborative processes. Diversity is defined as a property of a system containing elements apportioned to different categories (Stirling 2007). For example, if a team of collaborating individuals all work in the same location, their geographic diversity is lower than that of a team composed of individuals distributed across different locations. It has long been recognized that diversity in characteristics such as ethnicity and age within a team can influence its performance, suggesting multiple dimensions may be analytically relevant in explaining team creativity (McLeod, Lobel and Cox 1996). More recently, Boschma (2005) has proposed how several other dimensions such as geography and institutional context may influence knowledge intensive collaborations. Furthermore, there is a long tradition of work suggesting diverse individuals need to work together to undertake research on complex problems and for knowledge translation to occur during innovation (Laudel 2001; Joly et al. 2015). DARE seeks to build on these studies by providing a general approach for the analysis of diversity in research collaborations, in multiple dimensions, in the context of a trend in knowledge production in science, and technology for increased collaboration (Katz and Martin 1997; Wuchty, Jones and Uzzi 2007).

Teamwork provides creative opportunities by bringing together diverse individuals with different ideas, expertise, and resources, yet it is also associated with high costs related to coordination and communication (Guimerà et al. 2005; Cummings and Kiesler 2007; Wuchty, Jones and Uzzi 2007). Such difficulties can make the accomplishment of goals through collaborative research projects a substantial challenge and even lead some to question the effectiveness of such research investments (Stokols et al. 2008; Cooke and Hilton 2015). There is now a recognized need for new methods that can provide understanding at a micro level of how collaborative research leads to valued outcomes and impacts (MRC 2012; Cooke and Hilton 2015; Oancea, Florez Petour and Atkinson 2017).

The challenge of evaluating the contribution of interventions that take place a long way upstream from their potential societal impacts is not unique to research policy. For example, the attribution of impacts to specific policy measures has been indicated as problematic in other policy fields (Smutylo 2001). One of the ways in which evaluators have responded to this challenge is by focusing attention on the characteristics of early stage knowledge generation, application processes, and the intermediate outcomes they generate. A strand of research evaluation practice has emerged that focuses on processes (rather than outputs and impacts), such as the 'productive interactions' between researchers and non-academic stakeholders and how these are conducive to the generation of impacts (Molas-Gallart and Tang 2011; Spaapen and van Drooge 2011). A further contribution comes from Oancea, Florez Petour and Atkinson (2017), who focus on mapping networks established between researchers working on a project and stakeholders within and beyond their organization, identifying, and characterizing the information flows in the collaboration. The approach introduced in this article is located within this strand of research evaluation. We build on the notion that the potential effects of research investments depend on the interactions built among individuals during knowledge production or transfer. Yet, our proposal goes beyond current implementations of 'productive interactions' (better known as the SIAMPI approach) in that it does not treat every interaction equally. Diversity occurs across different dimensions and the 'distances' that need to be covered through the interactions differ too: sometimes a productive interaction will occur among agents sharing similar knowledge bases, or being geographically close. On other occasions cognitive, geographical, and other types of distance will make such interaction more difficult but also potentially more valuable. SIAMPI stops short of considering these issues, focusing on the nature of the interaction itself and the processes though which it occurs.

This strand of evaluation practice is also distinct from, and provides an additional perspective to, other approaches that analyse knowledge generation and application processes, such as those using an events-based approach to track progress in research or 'payback' of investments (Buxton and Hanney 1996; Trochim et al. 2011). Events-based approaches tell us little about how the different participants involved in the process have contributed to the outcomes and impacts that have been generated over time. To assess the contribution of a research project or, innovation programme, or to improve support for research it is necessary to understand whether and how diverse participants work together.

This article advocates the study of interactions between researchers and other participants during research collaborations as these interactions are the necessary and observable precursors of knowledge creation and application. Such interactions can be challenging because they require bringing together diverse participants who are members of different organizations and disciplines, and are motivated by different incentives that are potentially not aligned (Boschma 2005; Swan et al. 2007, 2010; Heinze and Kuhlmann 2008; Newell et al. 2008; Cooke and Hilton 2015). Whether and how these differences are bridged becomes a crucial evaluation question because if they are not addressed there is a risk that new knowledge formation will be impeded (Boschma 2005). In turn, the ability to study collaboration one dimension at a time, layer-by-layer, as well as combinations of dimensions can support fundamental understanding of research collaboration and formative evaluation processes. The contribution of each dimension to the whole can be studied to aid understanding of the links between patterns of interaction and desirable outcomes in research projects or programmes.

DARE provides a detailed basis for the analysis of research collaborations and can be used for longitudinal comparisons of particular relevance for evaluation studies. The next section introduces the concepts of diversity and cohesiveness, the key components of DARE. The methods used in the application of these concepts are explained in Section 3, while Section 4 presents two illustrations of how the approach can be used to study specific instances of research collaboration. The illustrations are presented as an initial operationalization to demonstrate that DARE can provide an informative description of collaborations, rather than with the aim of advancing theory. Section 5 discusses the potential applications of DARE and the practical and technical limitations apparent from its operationalization in its present form. Future opportunities for development of the method are also outlined.

2. Conceptualizing diversity in research collaborations

This section introduces the conceptual framework used in DARE for the study of interactions that occur in research collaborations. Diversity can be characterized in multiple dimensions and DARE is compatible with a wide range of possible dimensions of diversity. Indeed, it is a key tenet of the method that DARE can be used to integrate and distinguish between different forms of diversity in research collaborations, so as to provide a series of individually insightful perspectives on the same research effort. In this article, we use five dimensions introduced in a seminal article by the economic geographer Ron Boschma: *cognitive*, *organizational*, *social*, *institutional*, and *geographic* (set out in Table 1). Boschma proposed that these dimensions of distance (proximity) influence interactive learning and innovation (Boschma 2005).[1]

Molas-Gallart et al. (2016) draw on Boschma's framework and further propose that research investments seeking to foster collaboration should be assessed across these five dimensions as each can potentially highlight a different type of challenge to be overcome by the participants.

Participants can be closer in some dimensions, potentially presenting lower barriers to working together while at the same time being more distant in others. More distance suggests a greater bridging effort to overcome gaps but implies greater potential for bringing together more disparate knowledge.[2] The ability to observe and measure distance is a first step to understanding its impact on collaborations and their outcomes.

The conceptualization by Boschma (2005) characterizes relationships between individuals. Many studies that follow Boschma's framework characterize and analyse distances between pairs of individuals (dyadic interactions, e.g. Ponds, van Oort and Frenken 2007; Hardeman et al. 2015). While distance (proximity) can be used when discussing relationships between pairs of individuals (dyadic interactions), this concept is not applicable to the study of teams. What is required for the study of team dynamics is to characterize the network of interactions of the ensemble of participants to understand how they interact collectively. To this end, we will use the constructs of diversity and cohesiveness previously used to map 'knowledge integration' in interdisciplinary research (Ràfols et al. 2012; Ràfols 2014). We propose to use diversity and cohesiveness to describe the differences between individual team members and the extent to which they work together. These concepts are operationalized in the maps and indicators described below.

A key tenet of DARE is the important role of *cohesiveness* amongst those involved in a collaboration. Working relationships between distant individuals may be necessary and also challenging to establish and maintain. Therefore, an important objective to foster research collaboration may be to generate interactions between diverse individuals; when these interactions take place, the network then increases its cohesiveness. A given initiative can increase cohesiveness by establishing or strengthening links between distant participants.

DARE analyses collaborations in different dimensions, which require individual participants to be assigned to relevant categories for each dimension and links between individuals to be recorded (see Figure 1). The resulting diversity and cohesiveness measures are anticipated to vary by dimension and over time. This dynamic description of collaboration has been so far missing in evaluation of research, as critiqued by Balland, Boschma and Frenken (2015).

Table 1. Five distances that influence collaborative knowledge creation, following Boschma (2005)

Geographic distance	Geographic distance refers to spatial separation between actors. Spatial co-location facilitates the exchange of knowledge particularly in cases where knowledge is complex or difficult to transfer (such as tacit knowledge).
Cognitive distance	Cognitive distance refers to the extent to which actors differ in their knowledge bases. Some degree of cognitive similarity (i.e. a shared conceptual lexicon or agreed system of problem solving) is a prerequisite for interactive learning, as it facilitates communication.
Social distance	Social distance refers to the extent of relationships between actors, generally built on familiarity, friendship, and kinship. Where such relationships are close they facilitate empathy, communication, and coordination.
Organizational distance	Organizational distance refers to the separation of individuals by hierarchical structures, whether individuals are members of different parts of the same organization or members of different hierarchies in separate organizations.
Institutional distance	The institutional dimension refers to the norms, rules, and values that influence how actors behave. Large institutional distances may impose serious impediments to fruitful interactions if interacting actors respond to different, even potentially conflicting, sets of incentives or values.

Box 1. Mathematical operationalization of diversity and cohesiveness

(a) Diversity index (left, in terms of categories; right, in terms of individuals)	$\sum_{i,j} p_i p_j d_{ij} \Longleftrightarrow \sum_{k,l} \frac{1}{n^2} \delta_{kl}$
(b) Cohesiveness (left, in terms of categories; right, in terms of individuals)	$\sum_{i,j} i_{ij} d_{ij} \Longleftrightarrow \sum_{k,l} l_{kl} \delta_{kl}$
(c) Mean distance bridged (Cohesiveness/sum of intensities of interactions) (left, in terms of categories; right, in terms of individuals)	$\frac{\sum_{i,j=1}^{n} i_{i,j} d_{ij}}{\sum_{i,j=1}^{n} i_{i,j}} \Longleftrightarrow \sum_{i,j=1}^{n} p_{i,j} d_{i,j} \Longleftrightarrow \sum_{k,l=1}^{n} p_{k,l} \delta_{kl}$

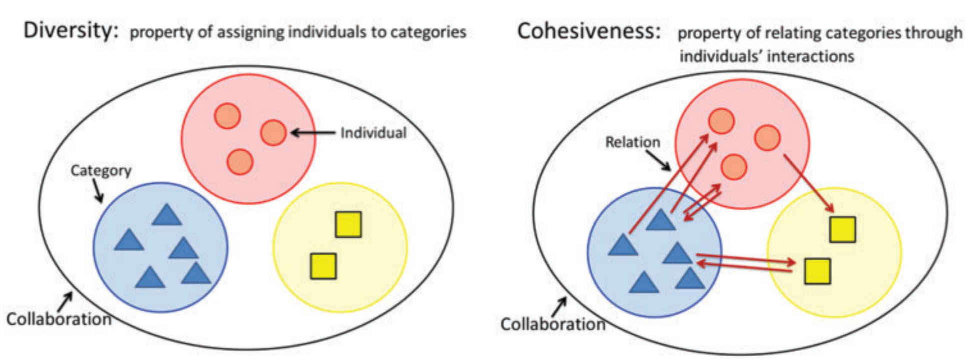

Figure 1. Illustration of diversity and cohesiveness of a collaboration for a given analytical dimension. Adapted from Ràfols (2014).

2.1 Measuring diversity and cohesiveness

Building on contributions by Stirling (2007) and Ràfols (2014), Box 1 describes the formulae used in DARE to measure diversity and cohesiveness. These form the basis of the network maps and indicators used in this article. A key difference between the proposed indicators and conventional network analysis (Wasserman and Faust 1994) is that DARE is concerned with node attributes rather than solely network structure. The diversity indicators used here rely on individuals' attributes, while the cohesiveness indicators rely on both individuals' attributes and the strength of individuals' interactions.

In the above formulae:

p_i is the proportion of individuals in category i,

$d_{i,j}$ is the distance between categories i and j,

n is the number of individuals,

δ_{kl} is the distance between the individual k and the individual l,

$i_{i,j}$ is the intensity of the interaction between the category i and category j,

I_{kl} is the intensity of the interaction between the individual k and the individual l,

$p_{i,j}$ is the proportion of the intensities of interactions between categories i, j, and

$p_{k,l}$ is the proportion of interactions between individuals k and l.

2.1.1 Diversity.

The diversity index used by Stirling (2007) and Ràfols (2014) provides an indicator describing how individuals are distributed across categories, accounting for the distances across these categories. Box 1(a) shows in mathematical terms the formula from Stirling (2007) where the distance (δ_{kl}) between individual k and individual l is defined as the distance (d_{ij}) between category i of individual k, and category j of individual l, while those in the same category are assigned a zero distance between them. In DARE, distances are assigned between individuals rather than categories so as to produce a more fine-grained description. This refinement is expressed in the second formula in Box 1(a). It is this second formula that is applied in DARE.

2.1.2 Cohesiveness.

In previous work, cohesiveness measured the intensity of interactions between categories (Ràfols 2014) while taking into account the distances between these categories.[3] The distance implies difficulty to interact between individuals in different categories, but also the potential to establish access to complementary experience.

In keeping with the diversity indicator above, the cohesiveness indicator presented here considers the interactions between pairs of individuals (rather than categories) taking into account the distance between them in a given dimension. Box 1(b) describes mathematically how cohesiveness is expressed both at the level of categories (as in Ràfols 2014) and at the individual level (in DARE) using the distance δ_{kl} that these interactions span.

A shortcoming of the cohesiveness measure resulting from the formulation in Box 1(b) is that the measure is not bounded, unlike diversity which is expressed as a value between 0 and 1; this may mean that high and low values cannot be discerned without comparators. The cohesiveness can be expected to increase as team size and diversity increases, even in the absence of links between distant categories. To recognize the establishment of links across more distant categories, a distinct normalized indicator is proposed, namely 'mean distance bridged', expressed in Box 1(c). The mean distance bridged represents the average distance across which individuals have interacted and can be interpreted in conjunction with the diversity indicator; if it is higher than the diversity indicator, this means that within this collaboration individuals have formed more links with team members in distant categories than in closer categories.

The cohesiveness indicator can be used at two or more distinct points in time to show the extent of the links created during a given research collaboration. By providing an account of the cohesiveness changes one can understand the specific efforts undertaken to bridge the distances, which in turn can provide an indication of the additionality of the project.

The following section details how one moves from these mathematical formulae to empirical measures and discusses difficulties and limitations encountered when applying these to practical examples.

3. Methods for applying diversity and cohesiveness

This section presents the methods used for the initial operationalization of DARE, starting with the rationale justifying the selection of the illustrative cases and followed by a discussion of data collection and analysis.

3.1 Sample selection

In keeping with prior work (Molas-Gallart et al. 2016), this article provides a step towards demonstrating the versatility of DARE through application within two examples. These have been selected deliberately to provide a contrast with each other in ways that DARE can distinguish. Thus, the cases vary substantially in the five dimensions defined in Table 1 as well as in other regards such as team size and funding duration. By selecting contrasting cases it is possible to show how DARE can help to distinguish between the characteristics and structures of research collaborations.

The two examples are both grant-funded projects that focus on 'translation' of biomedical research results into health-related applications. This emphasis on translation was chosen because this is an area where it was anticipated that research collaborations would involve diverse teams and where it has also been suggested that new evaluation approaches are required (Molas-Gallart et al. 2016).

Case 1 ('Biomarker analysis platform') involves a small team working across two organizations in the same country, spanning the divide between public and private sectors. This provides a window into university–industry collaboration, itself a topic of considerable academic and policy interest (Thune 2009; Bruneel, D'Este and Salter 2010; Perkmann et al. 2013). Key individuals in the project team shared social links prior to the project and most of the researchers involved shared their field of interest (oncology) prior to the project's commencement.

Case 2 ('Neglected disease epidemiology') involves a larger team of researchers working across many more organizations and spanning several low- and high-income countries. This project brought together researchers from a range of disciplines spanning the biomedical and geosciences. The organizations involved were all either part of the public sector or not-for-profit.[4]

The selection of research projects as the unit of analysis was motivated by the clear definition of the research collaboration with defined focus, identified team members, and a plan of activities all provisionally discussed in a research proposal (which was accessed for the DARE analysis). These projects also had clear start dates and project durations, providing the opportunity to analyse changes occurring after the start of the project.

3.2 Data collection

As stated above, DARE relies on three elements: narratives, maps, and indicators. Each of these has a role in providing an understanding of how individuals interact during research collaborations. Narratives provide contextual information on the interactions, including details of the challenges of knowledge production, as well as observations on the project that may be necessary to make sense of the maps and indicators. Maps provide a basis for intuitive insights about the diversities and changes in cohesiveness that occur during the collaboration. Finally, indicators give a synthetic insight and an aggregate indication of the extent of changes in interactions. These different ways of presenting data provide complementary perspectives, which are explored together in the results section. For each of these analytical elements, the main focus for data collection was interviews with project team members.

For both cases, the analysis started with an invitation to the project's Principal Investigator (PI) for an interview and a request to obtain a copy of the project proposal. In each case, initial discussion with the PI revealed changes to the staffing of the team between submission of the funding application and commencement of the award, as well as revealing informal links that broadened the collaboration.

Face-to-face interviews were conducted in each case with the PI and a post-doctoral researcher who was core to the project team. Interviews were then conducted by telephone with three further researchers for Case 1 and two for Case 2. Only a small proportion of the researchers involved in each project were interviewed. Although the optimal situation would be to have all researchers involved in a project report their interactions, when research teams are large this is often not practical. As a result, the maps and indicators used in DARE rely on team members recalling and disclosing their collaborative links. A selective approach was used to achieve some triangulation without becoming overly burdensome for the team being studied. When sampling interviewees from a wider network in this way, we made the assumption that it was most appropriate to start with those best placed to provide a comprehensive overview, and then move to those involved in smaller independent sub-groups. This assumption is motivated by the desire to gain access to a range of interviewees and also to have an early insight into the extent of the network to inform data gathering.

Interviews were recorded for accuracy, with the agreement of interviewees, but the names of all team members used in this article are pseudonyms to preserve anonymity. The research protocol was subject to ethical review and approved by C-REC, the appropriate institutional-level committee at the University of Sussex (Ref. ER/FL49/1).

3.3. Data gathering: using sketch maps as an interview aid

Verbally describing the multiple dimensions of numerous inter-individual links in a systematic manner presents a procedural challenge for interviewees and interviewers alike. For this reason, in face-to-face interviews the interviewees were encouraged to keep track of the links already discussed by drawing a sketch map of their collaborations. The sketch map approach used is similar in some respects to that applied by Oancea, Florez Petour and Atkinson (2017). However, Oancea and colleagues propose iterating the sketch maps they produced with the help of interviewees, resulting in an agreed map (based on qualitative data). In DARE, the emphasis is on converting the narrative account into quantitative data, which in turn supports the generation of a map and indicators using algorithms. In some cases, the resulting map may be similar to those drawn by interviewees, however the DARE approach removes some of the subjectivity of the interviewee (and interviewer) in rendering the structure of the maps, which may be produced in a standardized way. Figure 2 shows an example of a sketch map as drawn by an interviewee for one of the cases with names of individuals in the sketch obscured using a digital blurring technique in Figure 2 to preserve participant anonymity. Sketch maps proved to be a practical way to structure the discussion; they served as reference points that facilitated looping back to prior parts of the narrative, recalling missed points, and even on occasion aiding identification of major omissions (e.g. aiding recall of people previously not discussed).

Each sketch map features all participants in the research collaboration mentioned by the interviewee and records the host organization (represented by a bubble). The map shows which collaborators had ties pre-dating the start of the project—highlighted names (Figure 2). Some interviewees recorded additional information such as technical specializations, work developed after the project finished (such as new project proposals and scientific publications) and frequency of interactions. In other cases, this information was only provided orally. Organizational affiliation was also discussed and dual affiliations were noted and accommodated in the maps.

Telephone interviews provided a practical way to further document collaborative activity between dispersed teams. With the use of hand drawn maps precluded by this medium, telephone interviewees were asked to complete a matrix describing their relationships with other team members before the interview. This allowed telephone interviews to focus on their narrative account of the project and answer specific questions to address gaps left from other interviews.

3.4 Moving from qualitative to quantitative data

Interviews provided an opportunity for the interviewed team members to give a narrative account of the development of their research, the associated collaborations, its context, the challenges faced, the valued outcomes, and further (anticipated) outcomes of the research. During this account, the interviewees were invited to discuss their ties with other team members within the collaboration according to each of the dimensions of diversity studied. The description of these ties allows them to be transformed into quantitative data. The conventions used for assigning quantitative values in this first application of DARE are summarized in Table 2, and further described in the DARE user guide (Bone et al. 2017) along with full interview protocols. As Table 2 indicates, different approaches are demonstrated so as to generate the maps and indicators for each dimension.

Interview data alone were used for the geographic, organizational, institutional, and social dimensions. However, for the cognitive dimension, we used bibliographic data to describe the knowledge base of each individual participant and how it was influenced by the project, following previously established methods (Ràfols, Porter and Leydesdorff et al., 2010). This has the advantage of being able to estimate cognitive distances with reference to extensive bibliometric data providing a robust empirical basis for the analysis. Authors

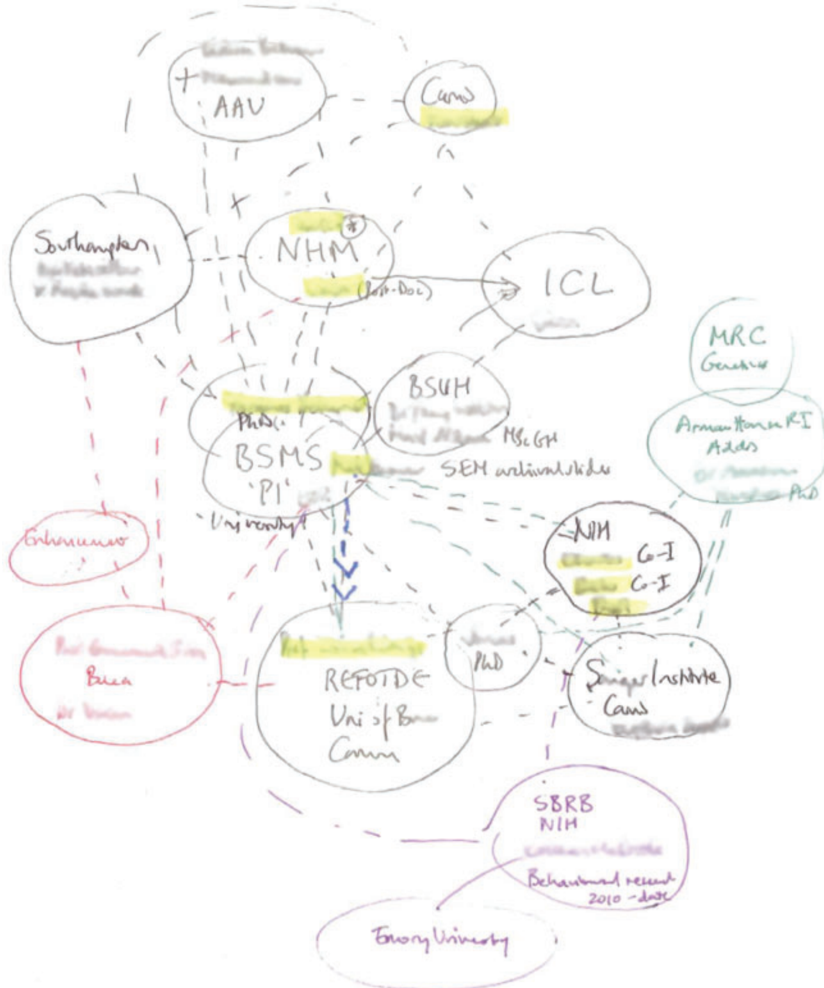

Figure 2. Drawings of project interactions produced by interviewees.

Table 2. Description of variables used for proof of concept operationalization of DARE

Dimension	Distance	Proxy used	Reference data	Prior literature
Cognitive	Distance on a continuous scale according to a WoS map of science	Cosine similarity using citations to journals associated with specific WoS categories	Distances between Web of Science Categories	Application as used in Râfols, Porter and Leydesdorff et al., (2010) on maps of science[9]
Geographic	Distance on a six-point scale: Same building, same campus, same city, same region, same continent, and different continent	Travel time between collaborating individuals' places of work	Estimated travel time	None used
Institutional	Five-point scale derived from the number of missions shared: Industrial, care, policy, education, and open science	Degree of overlap in the missions that collaborating organizations have calculated using the symmetric binary dissimilarity method (Han, Kamber and Pei 2012, 70–71)	None	Institutional categories are provided by Llopis and D'Este (2016)
Social	Three-point scale: strong, weak, or no relationship	Degree of acquaintance between two individuals	None	None used
Organizational	Three-point scale based on membership, partial membership, or no common membership of the same category	Membership of (one or more) organizational structures	None	None used

can be systematically positioned in cognitive space using the Web of Science subject categories (or other similar nodes within a global network of citations) as a proxy for their scientific experience and skills. Scientific fields that cite each other more rarely are characterized as cognitively more distant, and authors collaborating across these fields can be identified as engaging in comparatively rare bridging activities.

Assigning distances in the geographic dimension is empirically supported by observable spatial relations which can be measured in miles/kilometres or in travel time. Previous research suggests that propensity to collaborate is negatively correlated with distance in a non-linear manner (Kraut, Egido and Galegher 1988), so a non-linear scale may be appropriate for describing the efforts of bridging geographically dispersed teams. This reflects the finding that propensity to collaborate can drop off more quickly between labs in a building or buildings on a campus than between cities (ibid). For the purposes of our study, once an interviewee has identified a collaborator as being based in a given location, estimates of travel time between their locations were used (post-interview) to assign distance on a non-linear six-point scale. Collaborating researchers in the same building have a distance of 0 on this scale, while those on different continents have a distance of 1 (with those on the same campus, same city, same region, or same continent occupying points between 0 and 1).

Distance in the institutional dimension is assigned using a scale distinguishing institutions through how they differ in the extent to which their missions share one or more of the following: commercialization, care, open science, education, or policy (Llopis and D'Este 2016). The symmetric binary dissimilarity method (Han, Kamber and Pei 2012) is used to calculate institutional distance; here, two individuals exposed to missions with the same series of objectives (e.g. two universities focused on open science and education) would be defined as having an institutional distance of 0, while those that differ completely could have an institutional distance of 1 (although the maximum seen here is between a commercial business and a university–hospital which have a distance of 0.8).[5] This approach allows important distinctions to be made as individuals' institutional missions may not necessarily be the same as those of the organization they work within, for example university researchers may be embedded in hospitals for logistical reasons (Lander and Atkinson-Grosjean 2011).

Distances can be described with higher or lower granularity where there is a well-defined prior empirical or conceptual basis, but where this is lacking, a simple scale is used to illustrate an operationalization for the dimensions in question. For example, for the social and organizational dimensions, a three-point scale is employed to represent an interaction as present, partial, or absent. Distances in each dimension are expressed as a value between 0 and 1; for example, we describe organizational distance as follows: individuals working within the same department are assigned an organizational distance of 0, those working in a different department at the same organization have a distance of 0.5, and finally those in different organizations have a distance of 1.

A simple six-point scale was used to assign a value to interactions at interview ranging from an intensity of 0 (where individuals did not interact) to 1 (where individuals interact at least daily), with annual, bi-annual, monthly, and weekly meetings occupying other evenly spread points in the scale. Again, without reference data to support the design of the scale, this distribution of points is to some degree arbitrary and could benefit from calibration with future iterations of DARE.[6]

Using this operationalization of distances, maps are produced by first applying layout algorithms based on distances between individuals for each dimension. Once the layout has been set, the interactions between individuals are overlaid onto the graphs. The maps are produced using a force layout from the JavaScript library D3 (Bostock, Ogievetsky and Heer 2011). This specific library simultaneously enables push and pull forces between the nodes represented in the maps. This feature is particularly helpful since each pair of individuals is assigned a distance; when the distance is small, the pull force overtakes the push force and *vice versa*, aiding clearer visualization.

4. Analysis

This section illustrates how narratives, maps, and indicators can be combined in the operationalization of DARE. Each case starts with some narrative on the project drawn from interviewees and relevant documents such as research proposals; next, the diversity of the team and changes in cohesiveness in the period studied are analysed with the aid of maps that provide a visual representation of the collaboration, together with quantitative indicators that provide a synthetic overview.

4.1 Case 1: Biomarker analysis platform

4.1.1 Project narrative

Grant funding for 2 years was awarded to support the development of a biomarker analysis platform with the aim of providing insights into the activity of candidate drugs for the treatment of cancer. The project ultimately involved 12 individuals, all working in the UK at the time. Industrial scientists were involved to oversee application of the new biomarker platform to cancer drug development programmes owned by a pharmaceutical firm. Two academic research centres from the same university–hospital were also involved. One hosted the project PI and a novel analytical platform that was key to the project. The other centre provided access to the tumour samples on which the candidate drugs were tested.

The proposal was developed mainly by Mark and Oli with the help of Joe. Each were senior figures in their respective organizations.[7] Oli, who worked in a pharmaceutical firm, initially suggested to Mark that they collaborate on a funding application during a meeting at a conference. Within the window of time afforded by the conference they outlined the proposal; Mark was particularly interested in using the award to promote the work of Chris, a junior researcher, who was developing the analytical platform that the project centred on. Chris took the lead in the implementation of the project, while Mark and Joe played a supervisory role. Once the project had started Oli ultimately did not collaborate further with Mark or Chris but did maintain regular research meetings with the other research group at their university.

In retrospect, the project was deemed a success by the researchers involved. They valued the relationships and experiences that they had formed. Mark reported these links as the most valuable outcome of the project: '. . . putting different types of people and different skills together, I think that is so valuable and we need to do this more, we need to get out of our silos'.

Mary, an industry collaborator, confirmed the quality of the collaborative engagement from the pharmaceutical firm's perspective:

> '. . . there was a lot of collaborative work and good scientific discussion which is not always the case and there was a lot of

transparency in what was generated, good or bad, I think ultimately made it very successful and built a lot of trust on both sides'.

Flo, a post-doc on the project, further confirmed the novelty of the extensive interactions:

'The collaboration was the first time we [the two university-hospital research centres] worked together with a bigger group because before we always worked only with [Joe's] group … there would not be much of a collaboration before. But for this particular project there was a big interaction'.

Benefits were particularly experienced by the junior researchers, who worked across the two academic centres for the first time. This is indicated by an increase in social and organizational cohesiveness indicators (discussed below). The project also enabled many of the university researchers to work with industry for the first time. While most of the senior researchers had previously worked with industry, this was not the case for most of the junior researchers. This was a valued opportunity as Flo reported:

'It is always good to have the link with the pharmaceutical industry, because you can do different projects, you can do different things than just working on cell lines … … I wouldn't want to work just with cell lines for writing academic publications, I like more the clinical aspect as well, working with clinicians together with clinical trial samples and doing more assays which are more applied to patients as well'.

The analytical platform developed during Case 1 was adopted by other academic groups, aided by publications from the project. Subsequently, the platform became the basis for a university spin-out firm focused on providing services to pharmaceutical firms (not shown on the maps).

4.1.2 Project background: team diversity

The indicators in Table 3 provide an estimate of the diversity of the project team for each of the five DARE dimensions. Diversity observed in Case 1 is generally lower than in the neglected disease epidemiology case (discussed below). The project involves only two distinct organizations (a firm and a university–hospital), and three institutional types (firm, university, and hospital) out of a possible seven. The participants are all UK-based, albeit in two separate regions, and many of the researchers share their core discipline. The relatively small team size (twelve) also limits the potential upper boundary for the indicator of cohesiveness (further discussed below). Although the number of institutional types involved was limited, interviews revealed that the participation of individuals from different institutional types was crucial to the success of the project—in particular the inclusion of a clinician enabled access to the required bank of tumour cells.

The maps in Figure 3 give additional information about the diversity of the project team by displaying the distribution of nodes (individual researchers) across categories and space. The distance between nodes in the maps corresponds to their similarity with dissimilar nodes represented as more distant.

Features of the maps in Figure 3 are explained, dimension by dimension, to illustrate the value of studying these different perspectives of the same collaboration. In the organizational dimension the extent of links created between the firm and the university–hospital, and within the university–hospital are demonstrated (Figure 3a = before, Figure 3b = after), providing an indication of a valuable outcome for funders keen to foster university–industry links. The maps show that the outcome of the grant goes beyond reinforcing existing ties, with creation of many new ties that broaden the inter-organizational collaboration. In the institutional dimension (Figure 3c and d), individuals with duties spanning university and hospital institutional missions are included as separate categories; this is to distinguish between those research active participants who primarily have medical duties from those that have primarily university responsibilities. The maps show that only one individual had clinical responsibilities—potentially a limitation. In this particular case, the geographic dimension (Figure 3e and f) shows structural similarities to the maps representing the organizational and institutional maps (Figure 3a–d). However, the social dimension (Figure 3g and h) makes clearly visible how each member of the project team knew at least two others before the project started, with the exception of two team members brought into the network as a direct result of the grant (post-docs Flo and Tim). In the cognitive maps (Figure 3i and j), the shaded circles are used to aid visualization of some boundaries (but are not synonymous with the definition of categories in all cases). In this way, Figure 3i and j shows that the project's researchers are all active in the field of oncology, but also that their expertise spans biochemistry, molecular biology, and haematology. These cognitive fields are relatively proximate when compared to more distant knowledge domains such as physics, or the social sciences. For example, one participant's subjective perspective may be that they benefitted from working with 'quite a multi-disciplinary group'; this can be contrasted with more objective data that reveals the extent to which the links in this collaboration cross disciplines, as compared to a wider set of scientific activities as a frame of reference for different cases.

4.1.3 Project activities: team cohesiveness.

Indicators in Table 3 show this project increased cohesiveness amongst team members in all the dimensions, supporting participants' statements to this effect. While the strongest rise is in the social dimension, this simply indicates that many new interpersonal connections were formed. Perhaps more relevant from a funder's perspective is a large increase in mean distance bridged in the organizational, institutional, and geographic dimensions; this indicates

Table 3. DARE indicators for Case 1, the biomarker analysis platform

Analytical dimension	Diversity	Cohesiveness before	Cohesiveness after	Mean distance bridged before	Mean distance bridged after
Organizational	0.42	3.10	12.99	0.17	0.27
Institutional	0.25	1.91	6.57	0.10	0.14
Geographic	0.24	1.78	7.21	0.10	0.15
Social	0.80	3.60	34.65	0.20	0.72
Cognitive	0.13	1.84	6.20	0.10	0.13

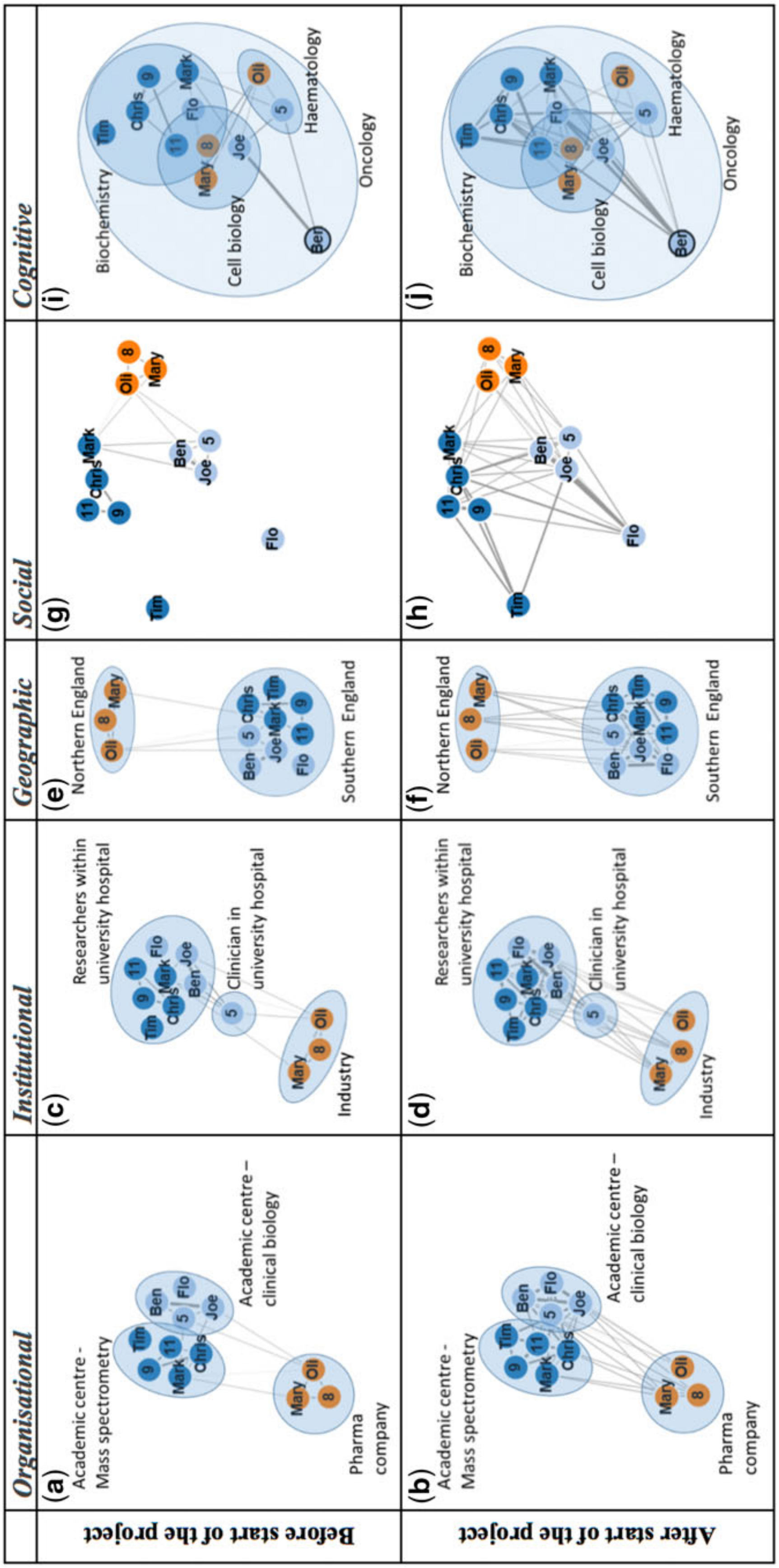

Figure 3. Maps in five dimensions showing collaboration networks for Case 1, the biomarker analysis platform.

that a number of boundary-spanning connections have been established, particularly due to the broad collaboration between a university–hospital and pharmaceutical firm. Yet in the cognitive dimension there is only a small increase in collaboration across cognitive boundaries, although a constraint may have been a lack of opportunity to collaborate with cognitively distant collaborators (i.e. the diversity of the team was low in this respect).

The maps add further nuance to the interviewees' accounts, revealing that although cohesiveness increased due to many new linkages being formed, the strongest linkages (shown by thicker lines) continued to be within categories (i.e. within an organization, institutional type, or region as shown in Figure 3b, d, and f). Cohesiveness is revealed clearly by the intensity of links shown in the social dimension maps (Figure 3g and h) revealing more intensive collaborations between those working within and across the two academic research centres. These individuals mostly knew each other before the project began, but the new team members (Flo and Tim) joining the university–hospital both formed strong links across the two academic groups involved. This provides quantitative support for the statement made by an interviewed team member suggesting a 'big interaction'.

4.1.4 DARE's added value.

The association of awards with outputs and outcomes is a formal requirement of the funder in this case. Thus it is on public record that the team's grant led to a series of standard outputs and outcomes including publications, a patent application, a university spin-out firm, a method (the novel analytical platform formally licensed to the spin-out firm), and follow-on funding awards. In this context, DARE provides information on the working relationships that supported these achievements with an accessible visual summary and helpful indicators of the extent of a collaboration with industry; this led to the development of a method deemed robust enough to form a spin-out firm, which in turn offered services of interest to several drug development companies. The spin-out firm, which involved Mark and Chris, was facilitated by Chris's experience with industry during this project. The mean distance bridged indicator shows that during the project, the team worked across organizational, institutional, and geographic boundaries and that, notably, the project relied on many new social connections. Yet the team was much less diverse in the cognitive dimension (the cognitive diversity indicator was 0.13 versus between 0.24 and 0.80 for the other dimensions). It is possible to speculate that this benefitted the team by providing some common understanding and thus support for bridging activities. The study of further similar cases could elucidate the importance of having less distance in one or more dimensions to compensate for greater distance in others, with possible implications for programme design or project team selection.

4.2 Case 2: Neglected disease epidemiology

4.2.1 Project narrative.

Ann had been studying a neglected disease while working at a university in East Africa. She then led the development of a successful funding application for a 5-year project to facilitate her move to a UK university while allowing continued work on the epidemiology of the disease. Ann built her project team using established collaborators and new contacts in East and West Africa, the USA, and the UK with the aim of studying both the environmental and genetic factors that caused the disease. To do so she planned to bring together expertise in geology, genetics, and medicine. At interview, members of the team highlighted the importance of the cognitive links created through the project, emphasizing these had made a key contribution to outcomes. Maria, a core post-doc on the project, expressed the uniqueness of the combination of disciplines brought together: 'As far as I understand, this project is one of the only examples of where this is ongoing, earth scientists and medical communities coming together to address something like this'. Jane, another post-doc on the project, also reflected on this interdisciplinarity and saw it as a strength: '...you need people from different backgrounds, you definitely need a geologist and need an epidemiologist but I think also including someone who understands epidemiology ***and*** spatial factors is also important'. [Emphasis added].

Maria noted that there were challenges in working with other disciplines:

> '... clay mineralogy is even a huge different subject than volcanology, that I am used to, and working with geostatisticians has been incredibly eye opening. The approaches that you would use to address an issue are extremely different from an earth scientist to an epidemiologist, and so we are looking at very different resolutions'.

Ann also described how she had to make sure she was able to work with both disciplines and develop a common language:

> '... we needed to talk the same language in terms of the type of strategy to be used. We used a lot of epidemiological terms, we had to make sure that that could be translated in terms that geologists could understand. Similarly, genetics has its own language as well, very technical. There is a bit of translation to do so that for example the geologists understand enough of that'.

She also saw her role as a connector and facilitator between people working in the two different disciplines: 'I suppose my role is different as I am not an expert in geology and so I can bow to other expertise, but trying to help people from this background linking to people without any geology understanding in epidemiology and health teams'.

As these quotes suggest, the project required expertise from different domains. Bridges between distant cognitive domains were created by several researchers other than the PI, Ann. Maria in particular created numerous connections which were important in accessing expertise from informal contributors, whose input played an important supporting role on the project.

Building connections between researchers across geographies was a key activity during this project, particularly between those working in the UK and Africa. Fieldwork trips to two geographically distant African countries were organized by Ann to collect data and soil samples, with the help of researchers from local universities. While formally based at Ann's medical school Eva, a PhD student, spent a large amount of time in Africa to complete the fieldwork. These trips enabled the team to build working collaborations for the project. These are visible on the maps, particularly through the geographic dimension (see below).

The project led to an extensive series of outcomes, including significant developments in understanding of the neglected disease leading to better treatments in the region studied.

4.2.2 Project background: team diversity. The team for Case 2 is substantially larger than in Case 1, with a total of 35 researchers taking part. A notable feature of the project is that only 17 of those involved in the research were formally associated with the project (i.e. named in the bid or formally hired to work on the project). Other participants had informal, but nonetheless important, roles. An example of an informal role during the project is the training of early career researchers in techniques required by the project. The scale of the network as it developed meant that core participants were not always aware of the contributions played by peripheral participants. This demonstrates the importance of conducting interviews with multiple participants to reveal the full network that have supported eventual outcomes. The maps in Figure 4 distinguish between formal and informal participants with nodes of different sizes. Larger nodes denote participants formally involved in the project (i.e. contracted to work with the PI), while those represented by smaller nodes played informal roles (ad-hoc collaborators).

The maps in Figure 4 display the distribution of individuals across categories in each of the five dimensions, while Table 4 shows the indicator values for each of the five dimensions of diversity. Notably, the diversity score is higher in each dimension for Case 2 when compared to Case 1. The dimensions with highest diversity indicator scores are the organizational and geographic, reflecting the distribution of the team across many different organizations and the spread of these across the globe. The organizational dimension maps (Figure 4a and b) show that 13 different organizations were involved in the project and that there was quite an even distribution of individuals across these. This generates the high value for the organizational diversity indicator in Table 4. The geographical dimension maps (Figure 4e and f) show a high concentration of individuals in the UK but the inclusion of participants in different continents (the USA and Africa) leads to a high indicator score for geographic diversity (see Table 4). The cognitive maps (Figure 4i and j) highlight that the project brought together individuals from both biomedical and earth sciences, with a variety of disciplines in each of these broad fields involved. The cognitive diversity indicator in Table 4 shows that the team is highly diverse (much more than in Case 1), supporting the reported experiences of the interviewed team members.

Figure 4c and d show the type of institutions that participants are aligned with. For instance, individuals with duties spanning university and hospital institutional missions are included as separate categories reflecting the diversity of their roles in Figure 4c . This allows us to distinguish between researchers primarily involved in research and those primarily involved in care, even when both are based in a hospital. This is important to represent because medics with greater time spent on care-related duties rather than research or teaching may find it harder to engage in research activities. The institutional diversity indicator in Table 4 is not as high as for the other dimensions in Case 2 (although it is slightly higher than the institutional diversity indicator for Case 1 shown in Table 3) because most of the participants worked at universities. Social diversity is also relatively high (see Table 4), reflecting a large team of collaborators who largely did not know each other before the project. This is visible in Figure 4g, which shows many unconnected individuals at the start of the project.

4.2.3 Project activities: team cohesiveness

Table 4 shows that the neglected disease epidemiology project led to large increases in the cohesiveness indicators in all dimensions. Increased cohesiveness is associated with the establishment of new links as well as intensification of existing links. In this case, the maps reveal that it is the creation of many new links that mainly contribute to increased cohesiveness. This is most visible in the social dimension maps (Figure 4g and h) which show the extent to which PI Ann and post-doc Maria increased their personal networks as a result of this grant. Cohesiveness is also higher for this case compared to Case 1, partly due to the higher number of individuals, but also the underlying diversity of this collaboration is higher.

Figure 4a and b shows that many inter-organizational links were formed. In particular, individuals such as Ann and Maria held positions in two organizations concurrently, which was explained at interview to be important for the progress of their work. In the institutional dimension, it is clear that many links also span boundaries (e.g. universities and university–hospitals working together) as well as with organizations that have a policy-focused mission such as NGOs and governmental organizations. In the geographic dimension, a large increase in the cohesiveness indicator reported in Table 4 is due to inter-continental collaboration between African and UK researchers as well as, to a lesser extent, researchers in the USA (as shown in Figure 4e and f).

The mean distance bridged indicator in Table 4 provides a simple summary of the extent to which boundaries were crossed in the different dimensions during the collaboration. These capture the substantial geographic bridging that the project achieved. Similarly, the mean distance for organizational and institutional dimensions increased suggesting the project facilitated the development of links across organizations and institutions more than it has encouraged collaboration within them. The extensive interdisciplinary work between biomedical and earth sciences is reflected in the rise in mean distance bridged in the cognitive dimension, while the mean distance bridged in the social dimension shows the strongest rise, emphasizing just how frequently individuals formed links beyond their prior networks as a result of the project.

4.2.4 DARE's added value.

Classic research evaluation, as required by the funder of this project, requires reporting of outputs and outcomes and reveals the extensive publications, follow-on funding, and details of the project's impact. The project informed scientific understanding of the diseases' causes and provided a significant stream of new publications to a relatively sparse prior literature. Awareness of the focal neglected disease was raised among local communities and internationally with resulting policy changes. Treatment regime and prevention strategy were developed, and these have subsequently benefitted tens of thousands of people. The DARE analysis shows how the project was catalytic by building a strong network that supported a series of further funded studies. In particular, the PI's success in engaging so many informal collaborators in Africa, the USA, and UK was an early sign of later progress, and one that would not be as clearly identified even by looking at publication outputs. DARE also provides a basis for supporting the team's claims about the extent to which the project created capacity enhancing North-South research links (much valued by the project's funder) as well as objectively recording the extent to which the project was interdisciplinary.

5. Discussion and conclusions

By building on prior concepts and frameworks by Boschma (2005), Stirling (2007), Ràfols (2014), and Molas-Gallart et al. (2016), DARE provides an original method combining narratives, maps, and indicators, to support a multi-dimensional analysis of teams

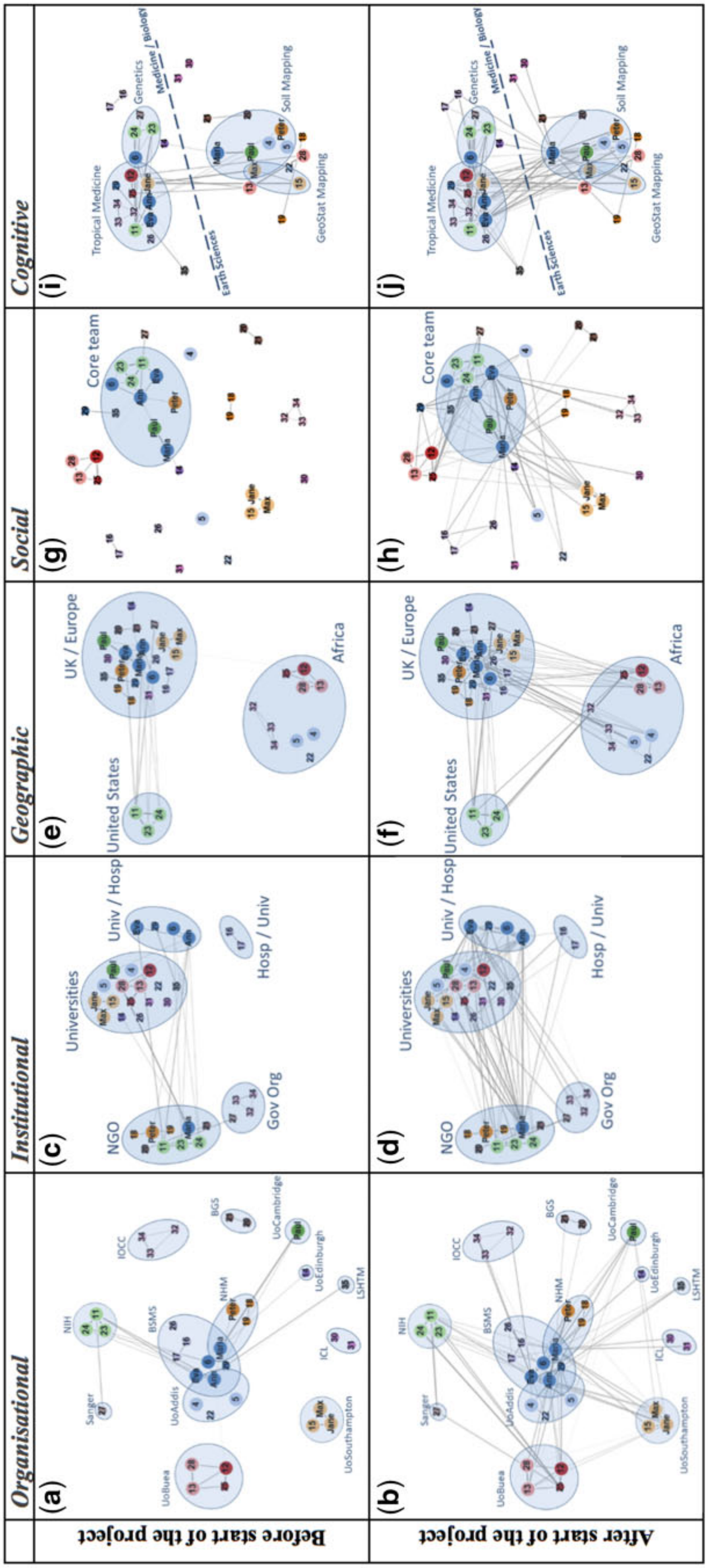

Figure 4. Maps in five dimensions showing collaboration networks for Case 2, neglected disease epidemiology.

Table 4. DARE indicators for Case 2, neglected disease epidemiology

Analytical dimension	Diversity	Cohesiveness before	Cohesiveness after	Mean distance bridged before	Mean distance bridged after
Organizational	0.90	15.40	96.40	0.41	0.64
Institutional	0.28	5.72	25.08	0.15	0.23
Geographic	0.74	11.92	57.12	0.32	0.53
Social	0.92	0.32	68.80	0.01	0.64
Cognitive	0.56	12.60	44.00	0.34	0.41

engaged in knowledge production and application. DARE emphasizes the importance of team diversity and the changing nature of links between individuals during collaboration. As such, it can inform the fundamental understanding of the role and contribution of diversity and cohesiveness in research collaborations. The method allows the extent of bridging efforts between diverse individuals to be determined and the relationship between these and subsequent outcomes to be studied.

The analysis in this article shows how two particular research grants each led to the formation of new team-based research collaborations that delivered valued outcomes. It shows the extent to which the two projects brought together diverse individuals, many of whom shared no prior connections, and the extent to which they combined expertise from different disciplines and organizations spanning different types of institutions and geographies. While such statements may often be made by teams, DARE provides a means to record claims about the diversity of the team and trace the efforts they made to work together. The two cases were selected because of their expected differences, and these are revealed by the analysis. Case 1 (the smaller team, working on a shorter project-based solely in the UK) clearly has lower indicator scores than Case 2 (a larger team, funded for more than twice as long in duration, working across three continents). More unexpectedly, the approach revealed the extent to which one team had recruited informal contributors during their project, as well as the large differences in cognitive diversity between the two projects. Also displayed are strong links that have been important for further work by both teams in very different ways. In Case 1, industry links provided vital experience that helped the core team members to start their own spin-out firm. In Case 2, the formation of an international network supported further research projects and ultimately led to improvements in the treatment of many thousands of people.

It is possible to see how these insights may be helpful to funders, to verify claims made by the teams they fund, or DARE could help to establish if the properties of a team meet the funder's criteria prior to funding. Once an award is in progress, DARE can be used to show early signs of progress in research collaborations even before outputs emerge. However, the application of the approach demonstrated here does not follow the studied collaborations beyond the term of funding, and so does not represent an attempt to follow a full pathway to impact. With a wider set of cases and a longer observation time frame, it may be possible to relate starting conditions (such as team diversity in particular dimensions) or processes (such as ways of enhancing cohesiveness) with outcomes. Furthermore, it may be possible to demonstrate that some level of diversity and cohesiveness is necessary to achieve particular outcomes. Yet, high levels of diversity or cohesiveness alone are not sufficient for outcomes to be achieved. As noted in Section 1, high levels of diversity can make progress in research collaborations difficult and cohesiveness may have an optimal level due to the time costs of establishing relationships, but beyond that, further links may not serve the outcomes of the project.

DARE provides a versatile new method for research evaluation. Research evaluation approaches can be described as configurative or aggregative; the former focuses on the processes used and values held by researchers and wider stakeholders, while the latter seeks to quantify impact or value created by initiatives (Oancea, Florez Petour and Atkinson 2017). DARE has elements of both these approaches as it aggregates data on interactions and also describes the characteristics of teams and the processes they follow in their collaboration. Another important distinction is between prospective and retrospective research evaluation modes (Oancea, Florez Petour and Atkinson 2017). While DARE is demonstrated in this article as a way to track changes retrospectively (while still potentially being able to detect informative changes earlier than post-hoc methods reliant on outputs), elements of DARE could be used prospectively for multi-dimensional characterization of research teams and their baseline cohesiveness.

Arguably, the versatility of DARE makes it broadly applicable, and with this objective in mind the following observations are made with a view to refining the approach for further use.

First, the five dimensions discussed here are not necessarily the only ones of interest in research evaluation. For example, dimensions such as gender, culture, or career stage could potentially be operationalized using the formulae developed and demonstrated here. There are technical and societal challenges to doing so, particularly with personal characteristics that may be protected in law and require appropriate consideration at every stage from data gathering to interpretation and reporting. The use of further dimensions may provide a more detailed understanding of the roles of these diversities in research collaborations, the challenges they pose and the ways in which these may interact, perhaps with low diversity in some dimensions compensating for challenges raised by high diversity in others (Boschma 2005).

Second, the method is flexible in terms of the timing of data collection and analysis. Data could be collected throughout the life of a collaboration or after it has finished. The 'start' and 'finish' comparisons (as used in Cases 1 and 2) may be of particular interest when evaluating specific interventions. Static or dynamic analysis of the structure of a particular research collaboration or broader network could be undertaken. This could be helpful for understanding attribution of outcomes and for understanding the benefits of particular ways of working together. In this way, DARE has the ability to track various interventions.

Third, it may be possible for DARE to be used with different types of data from those used here. For example, data routinely collected by funders or research organizations could be re-used for DARE, reducing the burden of new data collection in the application of DARE.

This initial application of DARE has highlighted some avenues for future exploration and some limitations to be addressed through further development. Future application could extend beyond the biomedical domain as there are no apparent conceptual reasons preventing this. Application beyond the short, team-based projects (Cases 1 and 2 were projects lasting 2 years and 5 years, respectively) is also theoretically possible. However, cases of longer duration or size require adequate resources for suitable analysis—or the DARE method requires adaptation to facilitate scaled-up data gathering. Some technical and practical limitations are discussed below as a first step towards further development of DARE.

Access to data: In this study, we used face-to-face and telephone interviews as the primary means of data gathering. For this to be possible, the analyst requires access to the core research team and their wider collaborators, some of whom may be very peripherally involved in the collaboration. Projects with many peripheral actors may be difficult to map if these individuals are difficult to engage and this could lead to measurement difficulties since second-hand reports of individuals' activities within a project are less desirable than primary accounts. In particular, these may affect the accuracy of the indicators that DARE uses. Of course, the more individuals that are engaged during data gathering, the more the indicators and maps will reflect the achievements of the research collaborations studied.

Robustness: Wider team involvement in data gathering can enhance accuracy of results through triangulation of observations, yet even with high coverage there are limitations to accuracy. When the studied researchers are active in one or more ongoing lines of research, it can be difficult to distinguish the individuals and activities that took place within the bounds of a particular project or initiative. This is particularly a problem when individuals are working on several projects simultaneously, or in a series of projects over an extended period of time, or where they are not formally part of the focal team. An iterative approach to data collection may be required, for example by clarifying details with the PI or core team members to determine the inclusion or exclusion of particular activities as comprising part of the initiative being studied. Norms for subject inclusion or exclusion at the boundaries of teams need to be developed in the analysis, particularly where comparative analysis of multiple teams is required.

Resources: In its present form, DARE is resource-intensive for the analyst as face-to-face interviews can take 90 min or more, particularly for core team members (although subsequently, 45 min telephone interviews with additional team members have been useful for gap filling and verification). Refinement of the interview instruments or development of a survey format, coupled with development of software interfaces to capture and analyse input data in a streamlined manner, could enhance efficiency by reducing the time burden of those being studied.

Availability of a frame of reference for dimensional scales: for some dimensions (such as the organizational and the social) the indicators used here are very coarse due to the lack of clear benchmarks for scaling. Further empirical evidence could help refine the indicators in these dimensions. Only in the cognitive dimension is it possible to judge whether the interactions in a given case are rare or common, with respect to a well-characterized broader population of collaborations described by the body of published research (as represented in this case by the Web of Science). Even here a limitation exists, in that team members with no publications (e.g. research assistants, students and early career researchers, or non-academic stakeholders) are difficult to place onto maps alongside those who have publication profiles. Interview methods could be used to generate a cognitive profile for those with no publications (e.g. allowing interviewees to identify subject categories that best describe their training) and might be matched against data on the prevalence of skills more generally. Likewise, reference data on the frequency of research collaborations across geographic distances for a large body of scientists could be used to calibrate scales used in that dimension. Until these frames of reference are assembled, application of the indicators may rely on qualitative estimates and comparisons across dimensions, for example in understanding the implications for trading off distance in one dimension with distance in another, as undertaken by Lander (2015).

Ambiguous categories: Some of the categories used to classify participants along the different dimensions may at times become unclear to the participants in a study. For instance, what is understood by the term 'department' can vary across contexts. In our pilot studies we did not encounter such difficulties, but researchers using this approach should be careful to ensure interviewees share their understanding of the terms used at interview. Basing the research on direct interviews (rather than written questionnaires) can help surface this kind of problems and clarify concepts if such difficulties emerge unexpectedly.

Cross-case comparisons: The availability of indicators invites quantitative comparisons between different cases; yet, without known outcomes from a wide range of comparator cases, it is not possible to make strong claims about the impact of diversity and cohesiveness on performance. If normative judgments are to be made on performance, care also needs to be taken to compare like with like, for example in terms of team size and project duration. Longer projects clearly provide more scope for cohesiveness and larger teams provide more scope for diversity and cohesiveness. With limited reference cases completed so far, DARE is best used for formative, rather than summative, evaluation. For example, DARE could be used to inform the redesign of funding programmes, based on case studies of funded projects that provide an understanding of whether and how the programme's design meets objectives such as spurring collaboration.

There is substantial interest in the role of distance (proximity) in innovation processes and much to be explored (Davids and Frenken 2018). Therefore, despite the limitations of DARE as presented in its prototypical form in this article, there may be substantial utility in applying the concepts of diversity and cohesiveness to the study of research collaborations. Central to this approach is a multidimensional view of collaborative processes that values the contribution of diversity, one that acknowledges the challenges it brings as well as the importance of understanding its role in knowledge creation and, ultimately, societal impact. It is anticipated that this approach will be useful in addressing a wide range of questions for the study of team science and other forms of collaborative interactions more broadly in academic, industrial, and policy contexts.

Data availability statement

The anonymized datasets generated during this study are available from the corresponding author on reasonable request.

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Conflict of interest statement. None declared.

Notes

1. While Boschma's work conceptualizes these dimensions in terms of 'proximity', here the term 'distance' is used to emphasize the gaps that are bridged during collaborations. Proximity and distance can simply be regarded as negatively correlated.
2. Boschma emphasizes that both too much and too little proximity between collaborating individuals can be detrimental to innovation and learning processes (Boschma 2005). Too little proximity makes it difficult to engage in interactive learning, and therefore, we should not take a normative position that a network displaying longer distances among its nodes is always 'better'.
3. Råfols (2014) (as well as related previous work) used the term *coherence*. Here we use *cohesiveness*, since it portrays better the notion of efforts to link or relate disparate expertise without necessarily suggesting the building of a logical or unified whole. We thank Richard Woolley and Taran Thune for discussions on this point within the OSIRIS Project (http://www.sv.uio.no/tik/english/research/projects/osiris/).
4. This case was volunteered by a co-author of this article. Since the focus of this article is merely a demonstration of the DARE approach (and not a formal evaluation of the performance of the teams in the cases studied), this selection is not deemed to present any conflict of interest by the authors.
5. See p. 15 in the DARE User Guide (Bone et al. 2017).
6. Further details of the methods used can be found in the DARE User Guide (Bone et al. 2017).
7. Individuals that were interviewed are assigned names—those that were not have been assigned numbers.
8. The underlying metrics are publicly available in Leydesdorff's website: https://www.leydesdorff.net/overlaytoolkit/.

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