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Assessing the variety of collaborative practices in translational research: An analysis of scientists' ego-networks

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Abstract

Translational research policies aim to reshape how biomedical scientists organize, conceive, and conduct science in order to accelerate healthcare improvements and medical innovations. Yet most analyses and evaluations of these initiatives focus on measuring the outputs generated in the different stages of the research process rather than observing scientists' research practices directly. In this article, we analyze the collaboration networks formed by the biomedical scientists participating in a large translational research initiative. Based on data derived from a large-scale survey, we examine the network configurations established by biomedical scientists to advance their research in the context of the CIBER program—a Spanish flagship initiative aimed at supporting translational research. We adopt an ego-network perspective and draw on three network attributes—network diversity, tie strength, and tie content—to understand how scientists use their interpersonal connections to mobilize tangible and intangible resources and enable the translation of scientific knowledge into practical applications. Our cluster analysis identifies a range of scientist profiles: downstream-oriented scientists, upstream-oriented scientists, and brokering scientists. It shows that the scientists participating in the CIBER program deploy different types of collaborative behavior and engage in a variety of medical innovation activities. This suggests that the results achieved by a research program aimed at supporting collaborative networks will depend on the types of networks in which the participating scientists engage. Consequently, evaluations of these programs need to capture collaboration patterns, and should focus primarily on the collaborative process rather than the outputs that emerge from the collaboration.

Keywords: social networks; translational research; research practices; interpersonal ties; medical innovation; brokerage

1. Introduction

In light of increased expectations about the socio-economic impact of research (Penfield et al. 2014; Reale et al. 2018), the focus of funding bodies has moved more and more to the demonstration of impact beyond academia. Thus, scientists applying to many public funding programs have to propose ex-ante impacts based on 'impact summaries' or 'pathways to impact' statements (Watermeyer 2016). Moreover, the idea of research quality has been expanded to include societal quality (Van der Meulen and Rip 2000) and ex-post impact evaluations are becoming integral to a range of funding contexts (Smit and Hessels 2021). This interest in socio-economic impact is reshaping how scientists organize, conceive, and conduct science (Marincola 2003; Zerhouni 2005; Rogowski, Hartz and John 2008).

The need to generate research results that respond to societal demands is particularly pressing in the biomedical field. We are witnessing an unprecedented period of research discoveries triggered by the rapid development of genome-related technologies, artificial intelligence applications, and massively increased data availability (Zerhouni 2005; Gittelman 2016). However, these exponential increases have not been matched by any systematic translation of research findings into practice and healthcare improvements (de Wilde et al. 2016). In fact, <10% of promising basic discoveries are licensed for clinical application, and only 3% of published research results progress to the clinical trial stage (Contopoulos-Ioannidis et al. 2003; Khoury et al. 2007; Maciulaitis et al. 2012). Actions to reduce the disconnect between lab and clinic have permeated policy agendas worldwide (see Aarden, Marelli and Blasimme 2021 for a review). Some ambitious US (Zerhouni 2003) and EU member states' initiatives (Billig et al. 2007; Eggermont et al. 2019) reflect this burgeoning interest among public funding agencies. Biomedical scientists are being encouraged to establish interdisciplinary research networks (Long et al. 2014), occupy intermediary research network positions (de Groot et al. 2021), or institute direct interactions with patients (Llopis and D'Este 2016) to generate medical innovations and healthcare improvements. These innovations can take multiple forms from product-related outputs (e.g. novel drugs) to process-oriented results (e.g. clinical guidelines) (Adler and Kwon 2013).

This reshaping of scientists' roles, priorities, and practices to include the delivery of socio-economic impact influences every stage in the research process (Olmos-Peñuela et al. 2015; Watermeyer 2016). However, most policy initiatives to accelerate healthcare improvements are based on a linear conceptualization of translational research (Rogers 2003) in which basic science informs and feeds clinical practice. This linear schema assumes the existence of 'translational gaps' which need to be addressed, and thus focuses on measuring

the outputs generated at different stages along the 'translational research continuum' rather than direct observation of scientists' research practices (Molas-Gallart et al. 2016). In this view, the main barrier to research translation is seen as the identification of the large divide between basic and clinical research which must be reduced in the successive stages of the translational research process (Van der Laan and Boenink 2015).

This linear and compartmentalized conceptualization of translational research often leads to evaluations that focus on specific events (i.e. outputs, outcomes) as indicating the achievement of a milestone in the translational continuum, and evidence that the barriers to its achievement have been overcome. A good example of this approach is Trochim et al. (2011), who propose the assessment of a translational research project based on the achievement of a series of milestones and the time taken to move from one milestone to the next. Other evaluation approaches focus on the analysis of academic publications (Grazier et al. 2013; Morillo et al. 2014) to infer the quality of the research results and identify collaborative patterns based on citations counts and bibliographic data.

What is common to this evaluative analyses on translational research is the focus on the specific outputs of the research process. In the present study we focus on the collaborative research practices that accompany translational research. We apply a set of analytical techniques derived from social network analysis to obtain a granular understanding of translational research. Some scholars suggest that close collaboration and knowledge flows among diverse actors from distinct professional settings are the cornerstone of the translational process (Lander and Atkinson-Grosjean 2011; Currie and White 2012; Crabu 2018). The implication is that medical innovation does not advance automatically from laboratory bench (basic) to patient bedside (applied). Rather, it is enabled by clinician-scientists operating at the intersection between science and care (Kluijtmans et al. 2017), and a greater focus on the bi-directional nature of knowledge and resource flows allowing basic scientists to feed on research questions from clinical practice (e.g. patient-inspired research). This is considered a core element of translational research (Marincola 2011).

It follows that there is a need to investigate how biomedical scientists involved in translational research collaborate (Long et al. 2014; Llopis, D'Este and Díaz-Faes 2021). By focusing on the collaborative practices, our analysis builds upon studies that emphasize the role of knowledge brokers (i.e. individuals who facilitate knowledge transfer between different knowledge domains and professional settings) in the translational research process (Lomas 2007; Lander and Atkinson-Grosjean 2011).

Our approach borrows concepts and indicators from social network studies and employs an ego-network approach (Phelps, Heidl and Wadhwa 2012; Borgatti, Brass and Halgin 2014) to provide a fine-grained picture of how biomedical scientists organize their collaborative practices. Our research setting is the biomedical research community in Spain, specifically a flagship initiative aimed at supporting translational research: the Biomedical Research Networking Centers (CIBER) program. The CIBER operates in different research areas and has specific goals which suggests that the collaborative processes associated with CIBER initiatives will differ across contexts. We conducted a large-scale survey to capture the variety of scientists' collaborative practices and participation in medical innovation activities. We explored the diversity of partners with which scientists interact (network diversity), the intensity of each interaction (tie strength), and the specific resource(s) channeled through each tie (tie content). Operationalization of these network concepts constitutes the primary data for this study. We performed a cluster analysis to group scientists based on similar collaborative practices and involvement in different medical innovation activities. The analysis identified three scientist profiles, each representing a different way of conducting collaborative biomedical research. We discuss the implications of our analysis and the differences it reveals in relation to the evaluation of translational research activities to support collaborative research.

2. Research practices and collaborative ties: an ego-network perspective

Interpersonal ties are crucial in biomedicine. Identifying research problems, designing lab experiments, collecting and analyzing data, and documenting findings often require formation of collaborative networks (Cannella and McFadyen 2016). At the same time, the development of research networks is crucial to catalyze the potential means by which (biomedical) science can generate impact beyond academia (Lomas 2007; Long et al. 2014; Kabo and Mashour 2019). For instance, the successful launch of a new venture (Davidsson and Honig 2003) and the capacity to generate creative ideas (Kijkuit and van den Ende 2007; McFadyen, Semadeni and Cannella 2009) depend in part, on the structure of the interpersonal connections among the actors. Scientists interpersonal networks often extend beyond the boundaries of the organizations in which they are embedded (Levin and Cross 2004; Perry-Smith and Shalley 2014), and involve exchanges with multiple individuals, which can be difficult to trace. In biomedicine, bridging the divide between diverse actors (e.g. basic scientists or medical practitioners) from distinct institutional settings (e.g. universities or hospitals) helps to reduce the gap between bench and bedside (Currie and White 2012; Díaz-Faes et al. 2020; Llopis and D'Este 2022).

The study of collaborative practices requires close observation of the heterogeneous attributes of scientists' collaborative ties, and an understanding of how these ties help mobilize tangible and intangible resources. We adopted an ego-network perspective allowing a focus on the individual (the 'ego'), the ego's direct ties with other individuals (the 'alters'), and the nature of these ties (Borgatti, Brass and Halgin 2014). In the following sub-sections, we discuss three ego-network attributes: diversity (connecting different professional communities), tie strength, and tie content.

2.1. Connecting professional communities: network diversity

Network diversity refers to differences among network members (Nahapiet and Ghoshal 1998). The literature shows that diverse networks allows the focal individual greater exposure to new knowledge, and the skills or abilities of their network partners (Burt 1995; Reagans and McEvily 2003). Network diversity can be grounded on network members job-related and/or demographic characteristics such as gender, ethnicity, experience, or knowledge basis. For instance, Boschma's (2005) proximity framework defines five types of proximity

(or distance) among individuals—cognitive, social, spatial, organizational, and institutional—and has been used to analyze diversity in research collaborations and dyadic interactions among network partners in the biomedical context (Bone et al. 2020). Cognitive distance is considered critical since diverse alters provide access to distinct knowledge stocks, resources, and frames of reference and increase the opportunities for knowledge recombination (Tindall, Cormier and Diani 2012; Tortoriello, Reagans and McEvily 2012).

One type of diversity which matters for translational research is professional diversity (Califf and Berglund 2010). Collaborative practices associated to bridging together individuals from different professional domains are an important source of network diversity (Currie and White 2012). For instance, collaborations involving biomedical scientists, medical practitioners, and patients lead to a greater variety of medical innovations (Llopis and D'Este 2016). This is because healthcare innovations often require resources and contextualized knowledge from different professions (Adler and Kwon 2013; Axler et al. 2018; Meseguer et al. 2022). Most translational initiatives require some reconfiguration of the professional and institutional barriers that separate fundamental research and healthcare (Goldblatt and Lee 2010; Lander and Atkinson-Grosjean 2011). However, research problems whose solution requires very specialized knowledge and expertise are likely to depend on homogeneous networks (Ter Wal et al. 2016), which facilitate effective flows of information and favor coordination based on reciprocity (Coleman 1988; Reagans and McEvily 2003). Therefore, considering the advantages associated to each of these network configurations, we expect that biomedical scientists' collaborative networks will differ depending on the range of professional communities involved.

2.2. Building strong and weak ties

Scientists seeking to adopt research practices conducive to the generation of socio-economic impact must decide how much time and energy to devote to building their networks. The scientist's capacity to build trust-based relationships with exchange partners based on common experience, shared meanings, and kinship is an important indicator of adoption of research practices related to translational research (Molas-Gallart et al. 2016). At the same time, the network literature points to the advantages of devoting limited efforts to interactions to enable access to distant social circles in order to promote creativity and innovation (Burt 1995; Levin, Walter and Murnighan 2011).

Network research suggests that the efforts devoted to interpersonal ties can be assessed based on tie strength and tie duration. Tie strength is defined as 'a (probably linear) combination of the amount of time, the emotional intensity, the intimacy (mutual confiding), and the reciprocal services which characterize the tie' (Granovetter 1973, p. 1361), and is rooted in a relational approach which focuses on the properties of the dyadic linkages between network partners (Borgatti and Cross 2003; Levin and Cross 2004). Some studies use interaction frequency to proxy for tie strength (Hansen 1999; McFadyen and Cannella 2004). Tie duration is measured as the length of time since the tie with the network partner was established. Although frequency and duration are different relational attributes, both measure the level of personal investment in the relationship (Cannella and McFadyen 2016).

Research on tie strength suggests there is no optimal configuration, and that both strong and weak ties provide the focal individual with different benefits. Weak ties provide access to non-redundant information by bridging between socially distant groups; their maintenance requires minimal time and energy and they provide efficiency and novelty benefits (Levin, Walter and Murnighan 2011; Tortoriello, Reagans and McEvily 2012). Strong ties facilitate reciprocity and foster the development of common goals, values, and language which result in trust and shared perspective. Some scholars suggest that a balance between weak and strong ties (Bruggeman 2016) is particularly useful for gathering highly complex knowledge. Therefore, we expect a heterogeneity of tie patterns based on the strength and frequency of scientists' dyadic ties to research partners.

2.3. Gathering instrumental resources: tie content

Network ties can act as conduits for multiple types of resources (Burt 1997; Sosa 2011). Studies adopting a tie content perspective focus on the variety of resources that can flow through interpersonal interactions. In this view, the tangible (e.g. financial, equipment, materials) and intangible (e.g. advice, advocacy) resources that focal individuals obtained through their interpersonal networks can be considered additional sources of heterogeneity at the dyad level.

Most of the literature adopting a social network lens in the academic context considers that the primary benefit derived from establishing an interpersonal network is a greater access to new information and insights (McFadyen, Semadeni and Cannella 2009; Phelps, Heidl and Wadhwa 2012). However, we know that network links are used to gain access to other resources than information and insights. For instance, Gómez-Solórzano, Tortoriello and Soda (2019) show that mutual trust and the support provided by interpersonal networks promote innovative behaviors among corporate R&D scientists. Cross and Sproull (2004) proposed the concept of 'actionable knowledge' to capture the different ways that interpersonal networks are used in projects. They show that interpersonal networks are used to get access to multiple resources, and distinguish among various components of actionable knowledge, ranging from specific solutions to legitimation. In a research setting, collaborative ties are also central to gathering valuable research resources such as data, materials, and specialized equipment. Using interpersonal networks is common practice in science to access specific materials and research funding (Mavris and Le Cam 2012).

The complex and diverse nature of medical innovation suggests that personal networks are crucial for providing access to complementary resources. For instance, some ties are critical for idea generation (Baer 2012) while others allow access to specialized expertise to translate ideas into concrete applications. Similarly, access to funding or specialized equipment might be as important as access to validation from stakeholders to enable the development of an idea (Perry-Smith and Mannucci 2017). Thus, collaborative practices and interpersonal ties might benefit biomedical scientists by providing access to a range of tangible and intangible resources to translate scientific knowledge into medical innovation.

3.Context and methods

3.1. Study context

The site of this study is the biomedical research community in Spain, specifically scientists participating in the CIBER program. This flagship initiative was launched by the Spanish

Ministry of Health in 2006 to reduce the translational gap across various biomedical specialties.[1] Pivotal to the CIBER program is enhancing research cooperation among scientists in different research groups and institutional settings (i.e. in universities, hospitals, public research organizations, firms, etc.), working on related pathologies. Research groups are selected through highly competitive open calls, focused on 12 areas of high priority for the Spanish National Health System[2]: Bioengineering, Biomaterials and Nanomedicine (BBN), Diabetes and Metabolic Associated Diseases (DEM), Epidemiology and Public Health (ESP), Hepatic and Digestive Diseases (EHD), Obesity and Nutrition (OBN), Mental Health (SAM), Neurodegenerative Diseases (NED), Rare Diseases (ER), Respiratory Diseases (ES), Cardiovascular Diseases (CV), Oncology (ONC), and Fragility and Healthy Aging (FES).

3.2. Sampling

We built a database using information available from the public CIBER directories.[3] This information allowed us to identify our survey population which includes 5,325 biomedical scientists (i.e. research group principal investigators, senior researchers, and early career and doctoral researchers), plus technicians and management support staff affiliated to the research groups. Between March to May 2018, we conducted nine interviews with CIBER scientific directors and research group principal investigators which allowed a better understanding of the biomedical context and enabled more adapted survey questions. Based on the information derived from the interviews we constructed a comprehensive list of items to capture medical innovation activities, and obtain a fine-grained perspective on the type of resources mobilized by biomedical scientists to advance their research.

The resulting questionnaire was organized in sections related to the scientists' networks. We adopted an ego-network approach (Rodan and Galunic 2004; Cannella and McFadyen 2016) and invited respondents to name up to ten contacts from outside their CIBER research group who were 'particularly important for the advancement of their research activities during the period 2016–7'. Respondents were then asked to answer a set of 'name interpreter' questions related to the contacts listed (i.e. network diversity, tie strength). We also asked respondents to indicate the specific resource(s) obtained from each alter (i.e. tie content). The survey also asked about the respondents' sociodemographic characteristics (e.g. age, gender, academic rank) and involvement in different types of innovation-related activities.

The questionnaire was administered via an online platform between June and September 2018. We received 1,616 responses, an overall response rate of 30.3%. Due to missing values for some questions, the number of valid responses was reduced to 1,146, an effective response rate of 21.5%, similar to that achieved by other surveys of academic scientists (D'Este and Patel 2007; Abreu and Grinevich 2013; Lawson et al. 2019). Based on the valid responses, the average network size was 3.63 and total number of network contacts reported by respondents was 4,160. The distribution of respondents by institutional affiliation was 27% from universities, 37.8% from hospitals/health sector organizations, 16% from public research organizations, 8.3% from non-profit organizations, and 10.9% other (firms, public administration, international organizations, associations). SPSS v.27 and Stata v.15 were used for the data analysis.

3.3. Indicators

3.3.1. Collaborative practices

Network diversity. Our name interpreter questions asked about the professional domain of the respondents' network contacts. We considered the following categories: (i) basic scientists; (ii) clinical scientists; (iii) medical practitioners, patients, and patient associations; and (iv) technicians, management support staff, and other professional fields. Based on the set of dyadic relationships in our data for which we have information on the professional domain of network partners, we found that most fall into the categories basic scientists (41.57%) and clinical scientists (37.16%) (see Table 1). However, our respondents also had ties to contacts in other professional domains such as medical practitioners, patients, and patient associations 6.53%, and technicians, management support staff, and contacts from other professional fields 14.75%.[4]

Tie strength. Following prior research (e.g. Tortoriello and Krackhardt 2010; Badir and O'Connor 2015), we consider two attributes related to tie strength: *contact frequency* and *tie duration*. *Contact frequency* was measured as average frequency of communication with each contact where 1 = 'one or several times per day', 2 = 'one or several times per week', 3 = 'one or several times per month', and 4 = 'one or several times per year'. Our dyad level data indicate that interaction is sporadic—only 13% indicated contact 'one or several times per day'. *Tie duration* captures the length of time the respondent and the contact had known each other. Levin, Walter and Murnighan (2011, p. 924) point out that 'almost anyone's life history will include an enormous number of interpersonal connections: some fleeting, some transitory, and others long-lasting'. The respondents were asked to indicate how long they had collaborated with each of their listed contacts: 1 = 'for 1 year'; 2 = 'between 1 and 3 years'; or 3 = 'more than 3 years'. The scores for tie duration show that most personal contacts are old acquaintances: 'more than 3 years' = 68.87% compared with 'for 1 year' = 6.27%. The patterns in Table 2 suggest an interesting mix of attributes; the prototypical personal network is composed of 'old' acquaintances consulted 'sporadically'. We therefore created two dummies for the cluster analysis: *long duration ties* and *low frequency ties*. The former represents contacts known to the respondent for more than three years; the latter denotes whether the interaction occurs 'once or several times per year'.

Tie content. To capture the range of tangible and intangible resources available from the scientist's personal network, we adapted the scale (see Appendix 1) developed by Cross and Sproull (2004) which was validated by Levin, Walter and Murnighan (2011) and Walter, Levin and Murnighan (2015). It has been suggested that dyadic relationships can contribute

Table 1. Distribution of network contacts by professional domain

Professional domain	Freq.	Percent
Basic scientist	1,725	41.56
Clinical scientist	1,542	37.16
Medical practitioner, patient and patient association	271	6.53
Technician and management support staff	612	14.75
Total	4,150	100.00

Note: Due to missing values for network diversity, the number of contacts per professional domain (n = 4,150) remains below the total reported (i.e. 4,160).

Table 2. Distribution of network contacts by contact frequency and tie duration

	Freq.	Percent
Contact frequency		
Once or several times per day	537	13.05
Once or several times per week	794	19.29
Once or several times per month	1,407	34.18
Once or several times per year	1,378	33.48
Total	4,116	100.00
Tie duration		
More than 3 years ago	2,821	68.87
Between 1 and 3 years ago	1,018	24.85
Since 1 year ago	257	6.28
Total	4,096	100.00

Note: Due to missing values for tie strength, the number of observations for contact frequency (n = 4,116) and tie duration (n = 4,096) remains below the total reported (i.e. 4,160).

Table 3. Absolute and relative frequency of different resources provided by network contacts

		Freq.	Percent
Intangible resources	Problem-solving	2,663	63.51
	New focus and problem reformulation	2,597	61.94
	Referral	1,779	42.43
	Validation (plans, ideas and solutions)	1,646	39.26
	Legitimacy	1,720	41.02
Tangible resources	Data and materials	1,702	40.59
	Techniques and equipment	1,770	42.21
	Funding	876	20.89

Note: Since each contact could provide between 1 and 7 resources, the total number of resources reported (14,753) is higher than the total number of contacts reported. Percentages refer to resources provided (at least once) by respondents' network contacts.

to the 'receipt of useful knowledge' along five dimensions: by providing specific solutions to problems or technical advice (*problem-solving*); by helping to define or re-frame a problem (*new focus and problem reformulation*); by suggesting other sources of information (people, archives, databases) not previously considered (*referral*); by validating plans and solutions and bolstering confidence (*validation*); and by legitimating ideas based on support from influential peers (*credibility*). Based on the information derived from our interviews, we added three more resources related to tangible assets: access to *data and materials* (e.g., patient data, samples, materials); access to *techniques and equipment*; and access to *funding*. Note that the provision of resources is not mutually exclusive for a given dyadic relationship: the same contact could provide up to eight different resources. Our dyad level data show that interactions with network contacts are related mostly to 'problem-solving' and 'new focus and problem reformulation' (63.51% and 61.94%, respectively) (see Table 3). Access to 'techniques and equipment' (42.21%) and 'data and materials' (40.59%) were also relatively frequent. This information allowed us to construct eight variables for the proportion of ties offering each of the eight resources to the focal respondent.

3.3.2. Participation in medical innovation activities

Healthcare innovations can take multiple forms including new treatments, improved diagnosis and prevention methods, and new healthcare delivery protocols (Sung et al. 2003; Khoury et al. 2007; Westfall, Mold and Fagnan 2007; Dougherty and Conway 2008). The development of new treatments depends on identifying new molecular targets for drug discoveries and their translation from the lab to specific human clinical research through clinical trials and observation studies (e.g. drug discovery and development) (Pisano 1997). New methods of disease diagnosis and prevention are associated with medical technologies such as new medical devices, equipment, and tests for early-stage diagnosis (e.g. genetic testing) (Hopkins 2006; Woelderink et al. 2006). Finally, medical practice can be improved through the development and adoption of new protocols for practitioners, patients, and the general public (e.g. clinical guidelines, public health policies) (Berwick 2003; Weisz et al. 2007; Adler and Kwon 2013).

To capture this variety, we identified 14 medical innovation activities (see Appendix 2). We asked respondents to report the frequency of their involvement in each of these innovation activities, in their research work during the period 2016–7. Respondents were provided with a drop-down menu from which they could choose between 0 and 10 times, or more than 10 times. We conducted exploratory factor analysis using principal component analysis for factor extraction and varimax as the rotation criterion.[5] The results show that our innovation-related activities can be categorized according to five latent factors[6] (see Appendix 2 for details) which account for more than 65% of the total variance: clinical guidelines, clinical trials, stakeholders' advice, commercialization, and patenting. Overall, 65.5% of our sample indicated having participated at least once in stakeholders' advice which was the most frequent activity followed by clinical trials (19.38%), clinical guidelines (17.23%), and patenting (11.99%). Participation in commercialization activities was less frequent, and reported by 3.87% of respondents.

3.4. Cluster analysis

We conducted a cluster analysis to identify groups of respondents based on personal network attributes and involvement in medical innovation. Cluster methods have been used in other healthcare and innovation studies (Bierly and Chakrabarti 1996; Proksch et al. 2019) and in social network research (Bensaou, Galunic and Jonczyk-Sédès 2014). From the 1,146 valid responses, the cluster analysis focused on the subset of respondents who reported at least one tie with contacts outside their CIBER research group (n = 908). Their average network size is 4.58, displaying an even distribution (i.e. interquartile range from 3 to 6 network contacts). Since our cluster variables are derived from the personal network, interaction with at least one network member was necessary to compute the variables.[7]

The cluster variables account for network diversity (*basic scientists*, *clinical scientists*, *practitioners and patients*, and *other*), tie strength (*long duration ties* and *low frequency ties*), tie content (*problem-solving*, *new focus and problem reformulation*, *referral*, *validation*, *legitimacy*, *data and materials*, *techniques and equipment*, and *funding*), and participation in medical innovation activities (*clinical guidelines*, *clinical trials*, *patenting*, and *commercialization*). We decided to exclude *stakeholders' advice* due to its limited discriminatory power: it was the most frequent output for 83.5% of respondents. Since cluster methods are sensitive to variables measured on

different scales, all our variables are considered as proportions. Note that we include total number of individuals in the personal network (*network size*) to account for size effects.[8] Appendix 3 provides the correlations for all the variables included in the cluster analysis.

We adopted a mixed approach. We used the centroids obtained using a hierarchical method to start a *K*-means algorithm (Milligan and Sokol 1980). Several researchers recommend the agglomerative Ward algorithm to determine the initial seeds for a *K*-means (see Steinley and Brusco 2007 for a comparison of different initialization procedures). We ran the Ward method on a random subsample of cases using squared Euclidean distances. The agglomeration schedule and the dendrogram show plausible cluster solutions ranging between three and four groups (see Appendix 4). Next, we performed *K*-means, using the cluster centroids derived from the Ward method as initial seeds. *K*-means is designed to partition *N* objects, each having measurements on *P* variables into *K* classes (C_1, C_2 ... C_K), where C_K is the set of n_k objects in cluster *k*, such that the within-cluster sum of the squares is minimized. Each object is assigned to its closest centroid, and the centroids in each cluster are recomputed until the process stabilizes (Steinley 2006). The three-cluster solution provides the most apparent and interpretable outcome.

4. Results

4.1. Cluster identification

Our cluster analysis approach identified three distinct scientist profiles: Cluster 1—36% of the cases (n = 327); Cluster 2—42.3% of the cases (n = 384); and Cluster 3—21.7% of the cases (n = 197). Table 4 presents the cluster centroids for the 19 variables describing the three network properties and the four medical innovation activities, for the archetypal biomedical scientist in each cluster across all the variables analyzed. To assess whether the distribution of collaborative practices and involvement in innovation differed significantly across clusters, we ran Kruskal–Wallis tests and post hoc comparisons using the Bonferroni correction (see Appendix 5), which adjusts the alpha level for multiple comparisons and so reduces Type I error (wrong rejection of the null hypothesis). We found that over 60% of the pairwise comparisons were significant at the 5% level. Therefore, the clusters show clear differences in terms of personal network attributes and medical innovation activities. However, some attributes apply similarly to all three profiles (e.g. 'referral' and 'validation').

4.2. Cluster discussion

To add meaning and improve interpretation of these emerging clusters, we characterized them based on the previously described key attributes. We labeled the clusters *downstream-oriented scientists* (C1), *upstream-oriented scientists* (C2), and *brokering scientists* (C3). Figure 1a–d depicts the main differences and similarities among the three clusters.

Cluster 1: Downstream-oriented scientists. This cluster includes 327 individuals, mostly scientists involved in innovations related to clinical practice since the most frequent medical innovation activities are clinical guidelines (29.8%) and clinical trials (28%). The scientists in this cluster have the highest proportion of clinical scientists in their personal networks (77%) and the lowest proportion of basic scientists (12.6%). In terms of tie strength, most contacts are old acquaintances (74.5% of long-lasting ties), and their interaction frequency is quite low (for 34% of the contacts, respondents meet 'one or several times per year'). This suggests that downstream oriented scientists rely on long-lasting connections whom they consult selectively. The resources accessed include new focus and problem reformulation (19.6%). Also, 14.1% of ties provide access to patients, samples, data, and/or materials. Demographic information from the questionnaire shows that the respondents in this cluster are primarily affiliated to hospitals (45.6%), with only 10.1% affiliated to public research organizations, confirming that these scientists are linked closely to clinical practice.

Cluster 2: Upstream-oriented scientists. For the 384 upstream-oriented scientists in Cluster 2, the most frequent innovation activity is patenting applications (17.3%). The members of this cluster have the highest level of participation in commercialization (4.5%). Few are involved in formulating clinical guidelines or participating in clinical trials; rather, they focus on invention and early-stage prototypes with commercial potential. Their networks include mostly basic scientists (78.2%). Most ties are long-lasting (66.3%) and are consulted infrequently (for 34.6%, 'one or several times per year'). These upstream-oriented scientists use their networks for problem-solving (21%) and problem reformulation (20.2%), while access to facilities, methodologies, analysis techniques and/or equipment are important tangible resources (14.4%). Overall, the results indicate that upstream-oriented scientists are more likely to conduct research that leads to discoveries and inventions with a commercial potential (i.e. patenting, licensing) than scientists in the other two clusters. In fact, this cluster includes the largest proportion of scientists affiliated to a university (37.5%) or a public research organization (20%), suggesting an orientation toward scientific discovery rather than clinical practice.

Cluster 3: Brokering scientists. The 197 scientists in this cluster display the most balanced distribution in terms of participation in all types of innovation activities: clinical trials 24.1%, clinical guidelines 15.7%, patenting 10%, and commercialization 3.5%. Compared with downstream and upstream scientists, their network ties are more evenly balanced between basic and clinical scientists and include in their networks the largest proportion of medical practitioners and patients (17%). Also, they have links with technicians, management staff, and individuals in other professional fields (56.7%), and tend to rely on well-established ties (62%). Compared with the members of the other two clusters they consult personal ties more often: only 20.2% of their contacts are 'low frequency ties'. They also show similar levels of access to a range of resources through personal interactions. Finally, brokering scientists are mainly embedded in hospitals (46.2%), following a distribution of institutional affiliations similar to downstream-oriented scientists.

5. Discussion

5.1. Biomedical scientists' collaborative practices

This article focuses on three network attributes to understand how scientists mobilize tangible and intangible resources through their interpersonal connections: network diversity, tie strength, and tie content. While the first refers to nodal properties based on the heterogeneity of network partners, the second and third refer to the dyadic properties of the personal

Table 4. Clusters centroids (averages) for three profiles identified

	Downstream (C_1) n = 327	*Upstream* (C_2) n = 384	*Brokering* (C_3) n = 197	*H* statistic	P-value	Pairwise comparisons
Network size	0.429	0.414	0.316	21.290	0.000	$C_1 \neq C_3$, $C_2 \neq C_3$
Network diversity						
Basic alters	0.126	0.782	0.150	659.177	0.000	$C_1 \neq C_2$, $C_2 \neq C_3$
Clinical alters	0.770	0.142	0.105	624.124	0.000	$C_1 \neq C_2$, $C_1 \neq C_3$
Practitioners and patients	0.048	0.027	0.175	46.990	0.000	$C_1 \neq C_3$, $C_2 \neq C_3$
Others	0.056	0.049	0.570	439.635	0.000	$C_1 \neq C_3$, $C_2 \neq C_3$
Tie strength						
Contact frequency[a]						
Low frequency ties	0.344	0.346	0.202	33.939	0.000	$C_1 \neq C_3$, $C_2 \neq C_3$
Tie duration[a]						
Long duration ties	0.745	0.663	0.620	16.484	0.000	$C_1 \neq C_2$, $C_1 \neq C_3$
Tie content						
Problem-solving	0.172	0.210	0.190	19.685	0.000	$C_1 \neq C_2$, $C_2 \neq C_3$
Problem reform.	0.196	0.202	0.170	15.672	0.000	$C_1 \neq C_3$, $C_2 \neq C_3$
Referral	0.116	0.109	0.118	0.904	0.636	–
Validation	0.099	0.093	0.100	1.885	0.390	–
Credibility	0.112	0.101	0.088	8.704	0.018	$C_1 \neq C_3$
Data and materials	0.147	0.095	0.141	31.194	0.000	$C_1 \neq C_2$, $C_1 \neq C_3$
Techniques and equip.	0.103	0.144	0.124	17.867	0.000	$C_1 \neq C_2$
Funding	0.057	0.046	0.070	6.674	0.036	$C_1 \neq C_2$
Medical innovation[a]						
Clinical guidelines	0.298	0.073	0.157	124.719	0.000	$C_1 \neq C_2$, $C_1 \neq C_3$, $C_2 \neq C_3$
Clinical trials	0.280	0.094	0.241	78.815	0.000	$C_1 \neq C_2$, $C_2 \neq C_3$
Patenting	0.070	0.173	0.100	12.541	0.002	$C_1 \neq C_2$
Commercialization	0.033	0.045	0.035	0.426	0.808	–

Kruskal–Wallis test including post hoc pairwise comparisons (n = 908).
[a] Note that for these variables, we do not include the remaining categories: contact frequency (i.e. *high frequency ties*), tie duration (i.e. *short duration ties*), and medical innovation (i.e. *no involvement in any medical innovation activity* and *stakeholders' advice*).

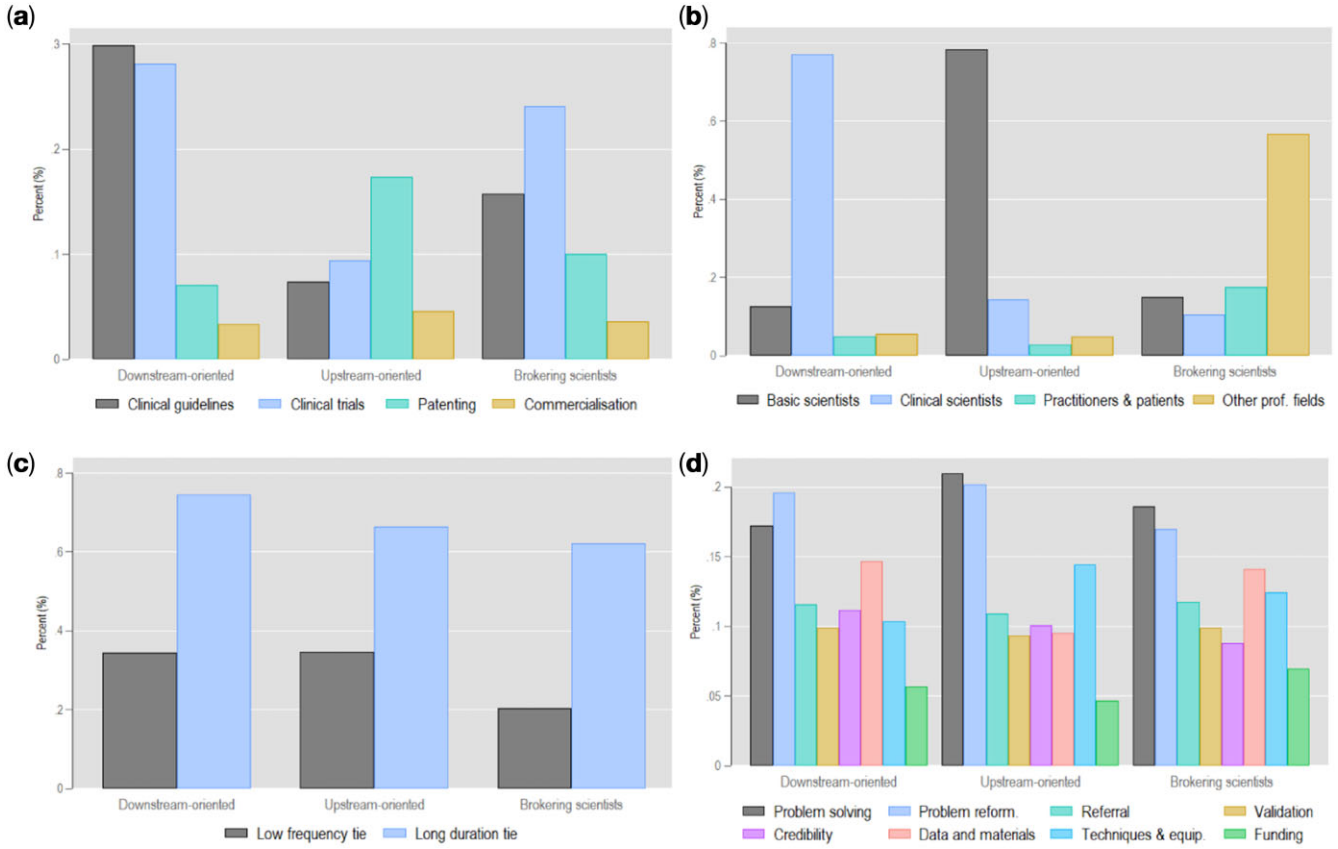

Figure 1. Cluster differences in medical innovation activities and network attributes. (a) Medical innovation; (b) network composition; (c) tie strength; and (d) tie content.

network. We argue that network diversity and tie content capture the distinct pockets of tangible and intangible resources, enhancing opportunities for resource complementarity and recombination. We suggest also that tie strength provides insights into the closeness of the relationship enabling knowledge exchange.

Our study identifies diverse collaborative practice profiles in the context of translational research, based on scientists' personal networks. On the one hand, high network diversity reflects research practices characterized by active collaboration with a range of academic and non-academic partners such as medical practitioners and patients or patient representatives who are potential research beneficiaries (Llopis and D'Este 2016). We found that high network diversity is linked to strong ties –that is, long-standing contacts who are consulted frequently. This resonates with discussion in network theory on the advantages of diversity combined with cohesion (e.g. tie strength). In this view, the benefits of high network diversity are enhanced by strong ties which enable cooperation and exploitation of different expertise and access to a range of resources (Reagans and McEvily 2003; Rost 2011; Clement, Shipilov and Galunic 2018; Bone et al., 2020). This supports the idea of resource complementarity facilitated by network diversity made actionable through the presence of strong ties (Ter Wal et al. 2016).

In contrast, scientists with homogeneous personal networks display connections with rather different dyadic properties. In this case, scientists rely on sporadic interactions with long-lasting ties which are maintained with little input of time or energy (Leana and van Buren 1999). These are described as weak ties, and provide novel insights and critical tangible resources. Network research suggests that while the low level of network diversity provides fewer opportunities for resource complementarity, it favors information processing and tie content triangulation between weak and strong ties (Ter Wal et al. 2016).

Our cluster analysis shows also that the distinct collaborative practice profiles differ in their orientation to innovation. *Downstream-oriented scientists* have highly homogeneous networks, interact mostly with clinical scientists, work in clinical settings, and tend to be involved in generating clinically oriented results. *Upstream-oriented scientist*s also have homogeneous networks that include mainly basic scientists, and typically, conduct research in non-clinical settings and produce inventions with significant commercial potential. *Brokering scientists* have highly heterogeneous networks and are more involved in a wide range of medical innovation activities. In terms of tie content, all three collaborative profiles display the capacity to mobilize similar ranges of resources with a predominant focus on 'problem-solving' and 'new focus and problem reformulation'. However, they differ in their capacity to or preferences for access to other resources: access to 'data and materials' is important for *downstream-oriented scientists*, and 'techniques and equipment' are prominent among *upstream-oriented scientists*, while *brokering scientists* assign similar importance to these resources. Finally, it could be argued that the distinct medical innovation engagement patterns to an extent reflect the opportunities for translation of research results into applications that is provided by the institutional context. Nearly 50% of *downstream-oriented scientists* are affiliated to hospitals and so are more hands-on regarding innovations in research practices (e.g. clinical guidelines), while almost 60% of *upstream-oriented scientists* work in universities or public research organizations, and are linked to more codified and fundamental research activities (i.e. patents, licensing).

Our study has some practical limitations. First, the survey population comprises researchers from a single country participating in a biomedical networking program. Although the CIBER program is at the heart of Spain's efforts to support translational research and includes several distinct biomedical domains and organizational environments, we cannot rule out that our results might be driven in part by the context. Second, our cross-sectional survey compares a range of biomedical scientists' collaborative practices but does not allow strong claims about the specificities of these practices for a particular medical specialty. Third, although the method used to capture personal networks is a well-established method in social network research (Borgatti, Brass and Halgin 2014), and allows access to fine details on personal networks, secondary data would test the robustness of our findings. Fourth, the survey respondents were asked to identify a subset of 10 relevant contacts from their entire personal network. Although average network size was around four contacts, and only 8% of respondents reported ties to 10 contacts, this methodological choice might overlook some meaningful dyadic interactions.

5.2. Implications for evaluation

The analysis in this article shows that the patterns of collaboration that emerge in connection with a translational research program vary. An ego-network approach has provided the conceptual and empirical grounds to identify such variety. The existence of varied patterns of collaboration suggests that the outcomes of translational research programs will be contingent on the type of networks they trigger or encourage. It follows that the evaluation of such programs would benefit from approaches that consider the (collaborative) processes through which knowledge and innovation are generated. Further, translational research policies similar to the ones addressed in this article are aimed specifically at changing the way research is conducted through the advancement of collaborative research across different types of participants. This calls for evaluations that focus on *how* the research is conducted.

Several studies encourage process-focused research evaluation approaches (Spaapen and van Drooge 2011; Reale et al. 2018), including those for the specific case of translational research evaluation (Molas-Gallart et al. 2016). This has led to the development of evaluation techniques such as the Diversity Approach to Research Evaluation (Bone et al. 2020) which provides a quantitative approximation of research team diversity and how much this diversity is bridged through active collaboration. The social network analysis tools deployed in this article could be applied also to ex-post research evaluation of translational research initiatives. They would provide empirical data on the social micro-foundations of research practices, and enable assessment of the extent to which policy interventions to support translational research are reflected in how biomedical scientists conduct research, and the specific patterns of engagement among diverse researcher and medical communities aimed at.

The findings of our cluster analysis show that an ego-network approach accounts for different forms of research conducted within a translational research initiative, suggesting critical network-related features underlying collaborative practices. Therefore, compared with a more conventional output-based approach which requires a single set of

measurable and comparable indicators of translational research 'output', our approach advocates for a granular understanding of the translational research process.

Notes

1. The Institute of Health Carlos III: *Consolider* programme, CIBER actions. BOE 94, April 19, 2007: 17366–17372. https://www.boe.es/diario_boe/txt.php?id=BOE-A-2007-8264.
2. In September 2021, a 13th research platform was added: Infectious Diseases (INFEC).
3. https://www.ciberisciii.es/en.
4. The low proportion of ties with these communities is not surprising; the survey was not aimed at capturing whether scientists had connections with medical practitioners, patients, or patient associations but rather which contacts had been critical for scientists' research.
5. A Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy (KMO = 0.806) and Bartlett's test of sphericity ($P < 0.001$) indicated that the data were suitable for latent structure detection.
6. Factor 1 explained 29.3% of the total variance and comprised development of guidelines for clinical practitioners and patients (*clinical guidelines*). Factor 2—outputs related to clinical trials (*clinical trials*)—13.79% of the variance; Factor 3—stakeholder consulting and advice (*stakeholders' advice*)—8.3% of the variance; Factor 4—commercial application of patents (*commercialization*)—7.71% of the variance; and Factor 5—inventions and patent applications (*patenting*)—6.22% of the variance.
7. The 238 respondents who reported no network contacts include a very low proportion of research group principal investigators and senior scientists (≈10%).
8. The original scale takes values from 1 to 10; we adapted it to range between 0 and 1 so that all our variables have the same scale.

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Appendix 1 Survey items capturing tie content

Tie content	Type of resource
Provided information and advice to solve specific problems that I found in my research	*Problem solving*
Provided a new focus to develop my research	*Problem reformulation*
Pointed me towards people and/or information sources that are relevant to my research	*Referral*
Helped me to improve my ability and confidence to explain and defend the scientific interest of my research	*Validation*
Made my research credible to third parties	*Credibility*
Provided access to patients, samples, data, and/or materials	*Data and materials*
Provided access to facilities, methodologies, analysis techniques, and/or equipment	*Techniques and equipment*
Provided access to funding to develop my research	*Funding*

Appendix 2 Exploratory factor analysis of medical innovation outputs (PCA used as extraction method—varimax rotation)

	Clinical guidelines	Clinical trials	Stakeholders' advice	Commercialization	Patenting
Development of treatment guidelines for patients	**0.834**	0.059	0.202	0.004	0.028
Development of guidelines or prevention protocols aimed at the general population	**0.809**	0.158	0.080	0.140	0.039
Development of clinical practice guidelines or protocols for clinical professionals	**0.666**	0.273	0.340	−0.102	0.132
Clinical trials phase I, II, III, or IV for new techniques and/or tools for diagnosis, prognosis, and response to treatments	0.121	**0.832**	0.243	0.017	0.088
Clinical trials phase I, II, III, or IV for drugs and substances for therapeutic use	0.135	**0.804**	0.219	−0.017	0.113
Design or execution of clinical trials for the repositioning of drugs	0.459	**0.571**	−0.044	0.088	0.040
Consulting and advice to patients, public administrations, or other non-academic actors	0.145	0.067	**0.807**	0.075	−0.013
Participation in observatories and/or groups of experts for the development of policies and action plans	0.343	0.181	**0.711**	−0.005	0.089
Collaboration agreements with companies, administrations, foundations, or associations of patients	0.038	0.312	**0.602**	0.246	0.160
Patents for which royalties derived from commercial exploitation have been received	0.008	0.026	0.099	**0.830**	−0.073
Granting of licenses derived from your patents	−0.003	0.030	0.121	**0.771**	0.320
Participation in companies originated from your research (spin-off)	0.130	−0.004	−0.010	**0.520**	0.404
Application for patents for medicines and substances for therapeutic use	0.069	0.045	0.009	0.085	**0.826**
Patent application for new techniques and/or tools for diagnosis, prognosis, and response to treatment	0.027	0.156	0.140	0.152	**0.680**

Note: Factor loadings > 0.500 are printed in bold. Factor 1 (clinical guidelines): 29.3% of the total variance; Factor 2 (clinical trials): 13.79%; Factor 3 (stakeholders' advice): 8.3%; Factor 4 (commercialization): 7.71% of the variance; and Factor 5 (patenting): 6.22%.

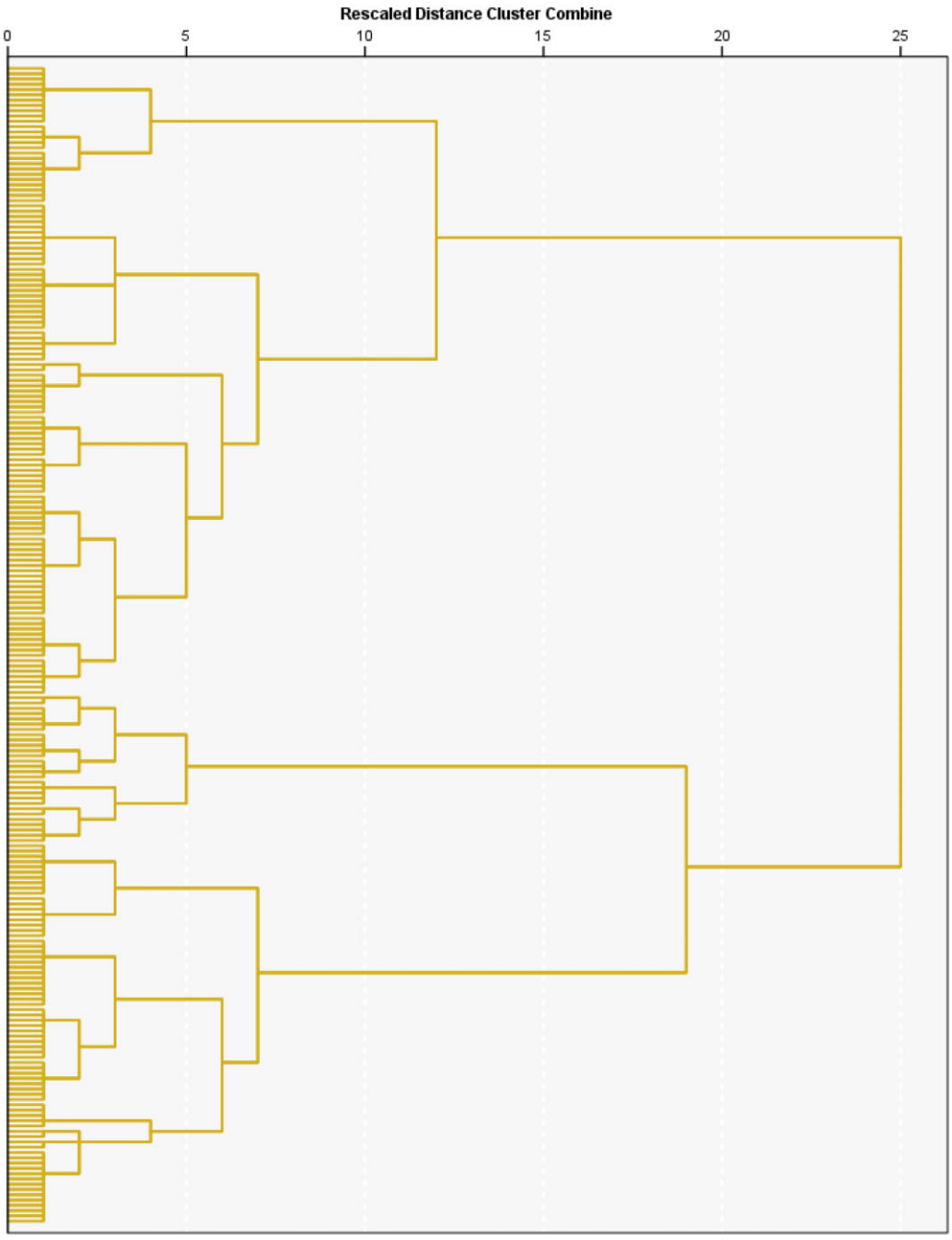
Appendix 3 Correlation matrix (n = 908)

		1	2	3	4	5	6	7	8	9	10
1	Network size	–									
2	Basic alters	0.53**	–								
3	Clinical alters	0.55**	−0.18**	–							
4	Practitioners and patients	0.20**	−0.13**	−0.02	–						
5	Others	0.28**	−0.15**	−0.07*	0.03	–					
6	Low frequency ties	0.56**	0.37**	0.35**	0.01	0.03	–				
7	Long duration ties	0.77**	0.37**	0.50**	0.12**	0.18**	0.41**	–			
8	Problem-solving	0.74**	0.47**	0.40**	0.09*	0.14**	0.32**	0.62**	–		
9	Problem reform.	0.75**	0.47**	0.45**	0.07*	0.08*	0.38**	0.65**	0.72**	–	
10	Referral	0.58**	0.24**	0.41**	0.09*	0.16**	0.23**	0.52**	0.59**	0.63**	–
11	Validation	0.54**	0.20**	0.39**	0.13**	0.13**	0.26**	0.46**	0.56**	0.61**	0.66**
12	Credibility	0.56**	0.24**	0.41**	0.07*	0.10**	0.26**	0.50**	0.56**	0.61**	0.67**
13	Data and materials	0.62**	0.18**	0.48**	0.26**	0.12**	0.34**	0.46**	0.45**	0.48**	0.50**
14	Techniques and equip.	0.63**	0.43**	0.29**	0.06	0.14**	0.34**	0.47**	0.58**	0.56**	0.53**
15	Funding	0.45**	0.17**	0.30**	0.07*	0.16**	0.24**	0.43**	0.38**	0.42**	0.52**
16	Clinical guidelines	0.01	−0.16**	0.17**	0.04	0.00	−0.06	0.09**	0.03	0.04	0.11**
17	Clinical trials	0.06	−0.14**	0.17**	0.09**	0.02	−0.09**	0.12**	0.07*	0.07*	0.08*
18	Patenting	0.03	0.02	−0.02	0.01	0.05	−0.02	0.07*	0.02	0.02	−0.03
19	Commercialization	0.10**	0.00	0.05	0.09**	0.08*	−0.01	0.10**	0.04	0.06	0.05

		11	12	13	14	15	16	17	18	19
11	Validation	–								
12	Credibility	0.76**	–							
13	Data and materials	0.48**	0.48**	–						
14	Techniques and equip.	0.53**	0.54**	0.51**	–					
15	Funding	0.44**	0.52**	0.44**	0.47**	–				
16	Clinical guidelines	0.10**	0.10**	0.05	0.00	0.03	–			
17	Clinical trials	0.09**	0.07*	0.08*	0.03	0.08*	0.49**	–		
18	Patenting	−0.02	0.00	−0.01	−0.01	0.03	0.15**	0.17**	–	
19	Commercialization	−0.01	0.06	0.05	0.03	0.08*	0.11**	0.11**	0.37**	–

* $P < 0.05$.
** $P < 0.01$.

Appendix 4 Dendrogram (using ward's linkage)



Appendix 5 Kruskal–Wallis post hoc tests values (Bonferroni correction) (n = 908)

Variables	Test Statistic	P-value	Variables	Test Statistic	P-value
Network size			Tie strength		
C_3–C_2	91.800	0.000	Low frequency ties		
C_3–C_1	101.209	0.000	C_3–C_1	116.337	0.000
C_2–C_1	9.409	1.000	C_3–C_2	121.696	0.000
Network diversity			C_1–C_2	−5.359	1.000
Basic scientists			Long duration ties		
C_1–C_3	−16.068	1.000	C_3–C_2	12.903	1.000
C_1–C_2	−449.080	0.000	C_3–C_1	78.962	0.002
C_3–C_2	433.012	0.000	C_2–C_1	66.060	0.002
Clinical scientists			Tie content		
C_3–C_2	38.809	0.249	Problem solving		
C_3–C_1	465.568	0.000	C_1–C_3	−20.465	1.000
C_2–C_1	426.759	0.000	C_1–C_2	−84.254	0.000
Practitioners and patients			C_3–C_2	63.789	0.016
C_2–C_1	30.401	0.063	Problem reform.		
C_2–C_3	−104.939	0.000	C_3–C_1	59.596	0.035
C_1–C_3	−74.538	0.000	C_3–C_2	90.885	0.000
Others			C_1–C_2	−31.290	0.337
C_2–C_1	11.411	1.000	Credibility		
C_2–C_3	−385.985	0.000	C_3–C_2	40.515	0.216
C_1–C_3	−374.574	0.000	C_3–C_1	65.882	0.013
Medical innovation			C_2–C_1	25.366	0.569
Clinical guidelines			Data and materials		
C_2–C_3	−64.237	0.002	C_2–C_3	−38.471	0.269
C_2–C_1	176.637	0.000	C_2–C_1	108.217	0.000
C_3–C_1	112.399	0.000	C_3–C_1	69.745	0.008
Clinical trials			Techniques and equip.		
C_2–C_3	−101.600	0.000	C_1–C_3	−27.353	0.731
C_2–C_1	138.657	0.000	C_1–C_2	−81.277	0.000
C_3–C_1	37.057	0.165	C_3–C_2	53.924	0.054
Patenting			Funding		
C_1–C_3	−21.894	0.567	C_2–C_3	−23.589	0.808
C_1–C_2	−49.072	0.001	C_2–C_1	47.329	0.029
C_3–C_2	27.178	0.280	C_3–C_1	23.740	0.840