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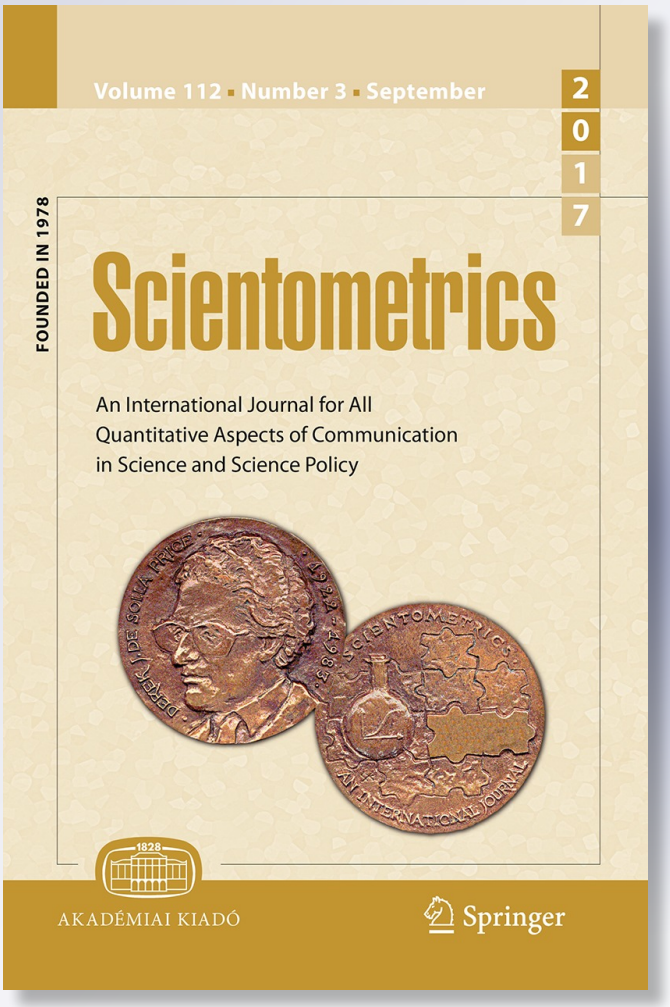

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Mapping the growing discipline of dissemination and implementation science in health

Wynne E. Norton[1] · Alina Lungeanu[2] · David A. Chambers[1] · Noshir Contractor[3]

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Abstract The field of dissemination and implementation (D&I) research in health has grown considerably in the past decade. Despite the potential for advancing the science, limited research has focused on mapping the field. We administered an online survey to individuals in the D&I field to assess participants' demographics and expertise, as well as engagement with journals and conferences, publications, and grants. A combined roster-nomination method was used to collect data on participants' advice networks and collaboration networks; participants' motivations for choosing collaborators was also assessed. Frequency and descriptive statistics were used to characterize the overall sample; network metrics were used to characterize both networks. Among a sub-sample of respondents who were researchers, regression analyses identified predictors of two metrics of academic performance (i.e., publications and funded grants). A total of 421 individuals completed the survey, representing a 30.75% response rate of eligible individuals. Most participants were White ($n = 343$), female ($n = 284$, 67.4%), and identified as a researcher ($n = 340$, 81%). Both the advice and the collaboration networks displayed characteristics of a small world network. The most important motivations for selecting collaborators were aligned with advancing the science (i.e., prior collaborators, strong reputation, and good collaborators) rather than relying on human proclivities for homophily, proximity, and friendship. Among a sub-sample of 295 researchers, expertise (individual predictor), status (advice network), and connectedness (collaboration network) were significant predictors of both metrics of academic performance. Network-based interventions can enhance collaboration and productivity; future research is needed to leverage these data to advance the field.

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Keywords Network science · Scientometrics · Implementation science · Dissemination science · Network analysis

Abbreviations

APA	American Psychological Association
APHA	American Public Health Association
D&I	Dissemination and Implementation
HMO	Health Maintenance Organization
IHI	Institute for Healthcare Improvement
IRI	Implementation Research Institute
MT-DIRC	Mentored Training in Dissemination and Implementation Research in Cancer
NCI	National Cancer Institute
NIH	National Institutes of Health
NIMH	National Institute of Mental Health
QUERI	Quality Enhancement Research Initiative
TIDIRH	Training in Dissemination and Implementation Research in Health
US	United States
VA	Veterans Affairs

Background

The scientific discipline of dissemination and implementation (D&I) research in health (including the related fields of knowledge translation and improvement science) has experienced increased interest and substantial growth in the past decade. There is a specialty journal (*Implementation Science*), scientific conferences and meetings (e.g., *Annual Conference on the Science of Dissemination and Implementation*, *Global Implementation Conference* (http://gic.globalimplementation.org/), training institutes (e.g., *Implementation Research Institute* [IRI (Proctor et al. 2013; Stamatakis et al. 2013)], *Knowledge Translation Canada Summer Institute* (http://ktclearinghouse.ca/ktcanada/education/summerinstitute), *Mentored Training in Dissemination and Implementation Research in Cancer* [MT-DIRC] (Brownson 2013), *Training in Dissemination and Implementation Research in Health* [TIDIRH] (Meissner et al. 2013), academic programs and courses (e.g., Health Implementation Science at Virginia Tech (http://www.tbmh.vt.edu/focus-areas/health-implement/index.html); a certificate program in implementation science at University of California, San Francisco (http://www.epibiostat.ucsf.edu/courses/implementation_research.html), professional societies (e.g., *Society for Implementation Research Collaboration* (https://www.societyforimplementationresearchcollaboration.org/); *Global Implementation Society* (http://gis.globalimplementation.org/) and webinar series (e.g., *National Cancer Institute's [NCI] Implementation Science Research Webinar Series* (https://cyberseminar.cancercontrolplanet.org/implementationscience/); Veterans Administration's (VA) *Quality Enhancement Research Initiative (QUERI) Implementation Seminar Series* (2015), most of which were nonexistent 10 years ago. While there are a plethora of terms (McKibbon et al. 2010) and considerable variation in conceptualization, D&I research, broadly speaking, is a scientific discipline focused on understanding and accelerating the integration of evidence-based practices, programs and interventions into routine health care and public health settings (Eccles et al. 2012; Eccles and Mittman 2006).

Unlike other, more specialized disciplines, D&I research cuts across scientific fields, methodological domains, delivery settings, and health content areas. While such diversity is important, and arguably necessary, it is increasingly difficult to appraise, synthesize, monitor and/or evaluate scientific progress across multiple areas, which may be exacerbated by funding silos and specialty outlets (e.g., journals, conferences) for sharing research findings.

Documenting, understanding and studying the growth of the scientific field of D&I is important for three reasons. First, it provides data to inform strategic planning to advance specific areas of inquiry (e.g., adaption of evidence-based practices (Chambers and Norton 2016); de-implementation of ineffective health practices and services (Norton et al. 2016; Niven et al. 2015). Second, it allows individuals who are new to the discipline to identify and understand its origins, including, for example, seminal papers, meetings, and thought leaders. Finally, it can highlight emerging problems (e.g., limited capacity in a content area; few mentors in a methodological domain) that could be addressed through targeted strategies (e.g., funding announcements, training programs, or support for new research teams).

Mapping is one method for capturing the existing status and subsequent growth of a scientific discipline. Mapping scientific fields has become increasingly accessible given advances in computing, information processing, and technology, and provide critical data on how a field emerges, develops (Herrera et al. 2010), flourishes, and/or disbands over time. These activities (Hood and Wilson 2001) are accomplished through a variety of methods, including (but not limited to) summaries of grant-funded research (e.g., portfolio analysis of cancer-related D&I research grants (Neta et al. 2015); portfolio analysis of NIH-wide D&I research grants (Tinkle et al. 2013); review of policy-related D&I grants (Purtle et al. 2016) systematic reviews of key components of the field (e.g., measurement instruments (Lewis et al. 2015; Rabin et al. 2012) and measurement repositories (Rabin et al. 2016) and analyses of collaboration networks (Herrera et al. 2010; Vanni et al. 2014).

One common approach is to map co-authorship (who co-authors with whom), citation (who cites whom), and co-citation (who is co-cited with whom by others) utilizing bibliometric methods; collaboration networks are also mapped by relying on surveys where individuals self-report and characterize their collaboration relationship with others. Indeed, and related to the field of D&I, Estabrooks et al. (2008) analyzed the structure of the field of knowledge utilization using author co-citation analysis from 1955 to 2004, providing a map of how the field changed and was influenced by key authors—most notably Everett Rogers—over time. Moreover, Estabrooks and colleagues mapped key authors in knowledge utilization and related terms (e.g., evidence-based medicine, diffusion of innovations, technology transfer), and reported a relatively small set of core authors within each domain and over time. Similar findings were also reported by Estabrooks et al. (2004) of a relatively small set of core authors in the field of research utilization in nursing.

While bibliometric methods are scalable (since the data already exist), in some situations, a survey-based self-report approach is more advantageous, as it can capture recent collaborative relationships, which given delays in publishing, are not part of the bibliometric data. Surveys are also better equipped to assess the quality and types of formal and informal collaboration relationships (e.g., mentor, mentee vs. co-author) not always captured in bibliometric data. This information is not only important for characterizing those in the field, and the field as a whole, but for strategically helping to guide the development of the field.

The current study focused on mapping individuals involved in the emerging field of D&I in health. To date, few efforts have been made to systematically map the field of D&I

in health, although Estabrooks et al. (2004, 2008) have mapped the related fields of knowledge utilization and research utilization using bibliometric analyses. No studies to date, however, and to the best of our knowledge, have mapped the field of D&I through primary data collection (vs. bibliometric) methodology. Specific objectives of the present study are four-fold: (1) to describe characteristics of individuals engaged in scientific discipline of D&I; (2) to identify engagement with common D&I resources (e.g., journals, conferences); (3) to characterize the dynamics of advice- and collaboration-networks; and (4) to identify individual- and network-level predictors of scientific performance, operationalized as (a) D&I publications and (b) receipt of D&I grant funding among a subsample of D&I researchers.

Methods

Participants

Eligible individuals included all 1419 subscribers to the *Dissemination and Implementation (D&I) in Health e-Newsletter* (which has since been re-named *Implementation Network*) as of October 2012. The *D&I in Health e-Newsletter* is a monthly e-newsletter and associated website that provides late-breaking information about D&I research in health to researchers, practitioners, and funders worldwide. The monthly distribution includes D&I article abstracts, job announcements, funding opportunities, webinars, conferences, resources, meetings, and/or training opportunities. The newsletter was founded in 2008 by one of the study authors (WEN) as a mechanism for sharing D&I information across health areas. The study was approved under exempt status by the Institutional Review Boards University where study authors resided at the time of data collection (WEN at the University of Alabama at Birmingham; AL and NSC at Northwestern University).

Procedure

All subscribers were sent an email inviting them to participate in the *Dissemination and Implementation in Health e-Newsletter Survey*, which included a link to the 15-min online survey. A for-profit company specializing in actionable people analytics, *Syndio* (formerly Syndio Social; https://synd.io/), administered the survey. Data collection occurred from October 2012 to December 2012. Individuals received email reminders approximately 2-, 4- and 6-weeks after the initial invitation. Participants who completed the survey were entered into a raffle drawing to win a 1-h consultation with a D&I expert.

Measures

Overview The online *D&I in Health e-Newsletter Survey* assessed (1) participant characteristics (e.g., demographics, involvement in D&I, scientific performance in D&I); (2) engagement with D&I journals and conferences; and (3) D&I advice- and collaboration-networks. Survey items were adapted from prior surveys on emerging disciplines (e.g., public health services and systems research (Merrill et al. 2011); oncofertility (Waimey et al. 2013) and pilot tested with a convenience sample of 8 D&I experts, including Fellows from the NIH- and VA-funded IRI (Proctor 2014) and expert faculty from the NIH-funded TIDIRH (Meissner et al. 2013).

Participant Characteristics Consistent with prior work (Merrill et al. 2011), we assessed demographic information (e.g., gender, age), primary professional role (e.g., researcher, practitioner), and organizational affiliation (e.g., academic institution, funding agency). Categorical and continuous responses options were provided (Merrill et al. 2011). To characterize participants' involvement in the field, we assessed years involved in D&I and level of D&I expertise (e.g., novice, intermediate, advanced, expert). To characterize participants' scientific performance, we assessed D&I publication in past 3 years (yes/no), number of D&I grant submissions, and number of D&I grants funded over the past 3 years.

Journals and Conferences Participants indicated the frequency (e.g., *Always, Sometimes, Never*) with which they accessed D&I articles among a pre-populated list of health journals. The default response option was set to '*Never*' to facilitate expeditious completion. Participants were asked if they attended any of a pre-populated list of D&I conferences over the past 3 years. For both questions, participants could add entries not otherwise listed. The initial lists of journals and conferences were compiled by one of the study authors (WEN) based on her experience identifying and collating D&I information for the e-Newsletter.

Advice and Collaboration Networks A combined roster-nomination method (Carrington et al. 2005; Wasserman and Faust 1994) was used to collect data on the D&I advice network and D&I collaboration network. This method was used to improve efficiency while protecting against low completion rates commonly associated with nomination-only approaches (Carrington et al. 2005; Wasserman and Faust 1994; Valente 2010). A roster (first name, last name) of the 1419 e-Newsletter subscribers was provided in list form; participants' own name was excluded from their list to avoid self-nomination. Participants were asked to select the names of individuals from whom they sought *advice* about D&I issues and, separately, with whom they *collaborated* on D&I activities. Importantly, and for both questions (asked separately), an open-text response option was made available so that participants could enter the names of individuals not already listed. The roster-list of names was searchable, as well, to expedite completion, and a 3-year recall period was used to reduce response burden (Merrill et al. 2011). Participants were asked how frequently (e.g., *Yearly, Quarterly, Monthly, Weekly*) they sought advice from and collaborated with each individual they selected. Finally, for the collaboration-network, participants were asked to indicate ('*Select all that apply*') their motivation(s) for choosing collaborators on D&I activities from a list of 15 statements that reflect 8 well established theories for building networks (Monge and Contractor 2003): uncertainty reduction, preferential attachment, resource dependency, collective action, homophily (i.e., similarity), trust, heterophily (i.e., diversity), and proximity.

Data analysis

To accomplish the first three study objectives, descriptive and frequency statistics characterized participants in terms of demographics and level of D&I expertise, and to identify common D&I journals utilized and conferences attended by participants. Network analyses (Carrington et al. 2005; Wasserman and Faust 1994; Monge and Contractor 2003; Hawe et al. 2004; Brass 2003) were used to characterize the D&I advice and the collaboration networks (separately) based on common network measures, including: (1) network measures attributed to individual actors and (2) network measures attributed to networks (Wasserman and Faust 1994). Measures used to describe individual actors reflecting a key position within each network included: *in-degree* for advice network and *degree* for collaboration network (i.e., number of incoming ties or links from other actors; popularity

position), *betweenness centrality* (i.e., extent that the individual falls on the shortest path between other pairs of individuals in the network; brokerage position), and *eigenvector centrality* (i.e., extent to which an individual is connected to a lot of individuals who are connected to a lot of individuals; prestige position) (Wasserman and Faust 1994; Monge and Contractor 2003). Measures used to describe the D&I advice and collaboration networks (separately) included: *size* (i.e., number of actors or nodes in the network), *ties* (i.e., links between nodes), *isolates* (i.e., nodes that have neither a direct nor indirect tie to any other node), *density* (i.e., ratio of the number of actual links to the number of possible links in the network), *biggest component* (i.e., largest number of individuals who are connected to one another via direct or indirect ties), *average geodesic distance* (i.e., average of the minimum number of steps or 'degrees of separation' connecting any two individuals), and *clustering coefficient* (i.e., closure within an individual's network) (Wasserman and Faust 1994; Monge and Contractor 2003). Participants' motivation for collaboration on D&I activities was reported by total count ('*Select all that reply*') for each of the 15 statements that reflect 8 established theories for building networks (Monge and Contractor 2003).

To accomplish the fourth study objective, regression analyses identified individual- (e.g., age, gender, level of D&I expertise) and network-level (i.e., advice and collaboration networks) predictors of two common metrics of scientific performance: (1) publication and (2) grant funding. Consistent with prior operationalizations of academic performance (Merrill et al. 2011) and to facilitate recall and accuracy of responses given the likely range in number, publication was assessed as a dichotomous variable as having published (first author or co-author) at least one (vs. none) D&I article over the past 3 years. Consistent with prior operationalizations of academic performance (Merrill et al. 2011), grant funding was operationalized as (a) number of D&I grants awarded (continuous variable) and (b) ratio of awarded-to-submitted (i.e., 'hit rate') D&I grants over the past 3 years. For this analysis, we restricted the sample to respondents who provided complete data and who identified their primary professional role as that of a researcher ($n = 295$ of the overall 340 researchers), since peer-reviewed publications and grant funding are the most appropriate performance metrics only in the research enterprise. Probit regression analyses with maximum likelihood estimation (MLE) assuming normal distribution of errors were used to identify predictors of peer-reviewed publication. McFadden's rho-squared (i.e., pseudo R^2) was computed, where values of 0.2–0.4 represent excellent fit (McFadden 1973). Ordinary least squares (OLS) regression analyses were used to identify predictors of grant funding (both number of grants funded and ratio of funded-to-submitted, respectively). Network analyses were performed in RStudio (Version 0.98.109© 2009-2014, RStudio, Inc.) using the package *SNA: Tools for Social Network Analysis*. Scientific performance analyses were performed in STATA 13.1 (StatCorp, LP).

Results

Participant characteristics

A total of 1419 individuals were invited to participate in the online survey; 50 email addresses bounced or were non-existent, resulting in a final sample size of $N = 1369$. Of the full sample, 156 provided limited data (i.e., only responded to one or two items); 421 completed most or all the survey items. Thus, analyses for the present study were restricted to the 421 participants who provided responses to the majority of survey items, representing 30.75% of the eligible sample.

As displayed in Table 1, many participants were female ($n = 284$, 67.4%) and White ($n = 343$, 81.4%). Frequent responses for educational attainment ('*Select all that apply*') included a Master's degree (e.g., MS, MA; $n = 223$, 53%) and a Doctoral degree (e.g., PhD, DrPH; $n = 248$; 58.9%); fewer participants reported having clinical degrees (e.g., NP, RN; $n = 19$, 4.5%; e.g., MD, DO; $n = 47$, 11.2%). Most participants identified their primary professional role as that of a researcher ($n = 340$, 80.7%), with fewer practitioners ($n = 54$, 12.8%) and funding agency representatives ($n = 23$, 5.4%). Self-described D&I expertise level varied across the response categories of Novice ($n = 100$, 24%), Intermediate ($n = 193$, 46%), Advanced ($n = 72$, 17%) and Expert ($n = 29$, 7%). Participants reported conducting most D&I activities in the United States (US; $n = 310$), with fewer in Canada ($n = 21$), United Kingdom (UK; $n = 11$), South Africa ($n = 8$) and India ($n = 7$). An additional 48 countries were selected—mostly low- and middle-income countries—with 5 or fewer participants reported conducting D&I activities per country. Primary organizational affiliation included academic institutions, funding agencies, health care

Table 1 Participant characteristics ($N = 421$)

Variable	*N* (% of total)
Gender	
Female	284 (67.4%)
Male	121 (28.7%)
Race/ethnicity[a]	
White	343
Other[b]	70
Age	
39 or younger	123 (29%)
40–49	110 (26%)
50 or older	142 (34%)
Primary professional role	
Researcher	340 (81%)
Practitioner	54 (13%)
Funder	23 (5%)
Educational attainment[a]	
Bachelor's degree or less	137
Master's degree (e.g., MS, MA)	223
Doctoral degree (e.g., PhD, DrPH)	248
Nursing degree (e.g., NP, RN)	19
Medical degree (e.g., MD, DO)	47
Initial involvement in D&I	
Before 2000	65 (15%)
2000–2009	221 (52%)
2010 or Later	122 (29%)
D&I expertise	
Novice	100 (24%)
Intermediate	193 (46%)
Advanced	72 (17%)
Expert	29 (7%)

[a] Select all that apply response option; percentages not included

[b] Due to small sample sizes, we collapsed non-White responses (e.g., African-American, Asian, Hispanic) into a single 'Other' category. Percentages may not add up to 100% due to 'prefer not to answer' response option (data not shown)

organizations, non-profit organizations, and health departments. Among participants, organizational affiliation was highest in the US Department of Veterans Affairs (VA; $n = 56$), followed by the Washington University in St. Louis ($n = 15$), and the United States Centers for Disease Control and Prevention (CDC; $n = 11$).

Journals and conferences

Table 2 displays the frequency with which participants reported finding D&I articles in a variety of health-focused journals, listing the top 20 (out of 57 total) journals most frequently reported. As expected, the preeminent journal, *Implementation Science*, was ranked first: 197 participants reported that they '*Always*' found D&I articles in the journal. Journals in the top quartile were generally more public health-focused (e.g., *American Journal of Public Health, American Journal of Preventive Medicine*) while those in the bottom quartile were more health care-focused (e.g., *Journal of American Medical Association [JAMA], BMJ Quality and Safety*). Interestingly, of the top 20 journals identified by participants herein, only two (e.g., *JAMA* and *Medical Care*) were identified by Estabrooks et al. (2008) as prolific publishers of articles in the related field of knowledge utilization from 1955 to 2004. No overlap was seen in the top 20 journals identified by participants herein and those identified as frequent publishers of research utilization in nursing, respectively (Estabrooks et al. 2004). Table 2 also presents frequency of attendance at various D&I conferences within the past 3 years. Unsurprisingly, attendance was highest at the *NIH Annual Conference on the Science of Dissemination and Implementation Research in Health* ($n = 207$) and lowest among smaller conferences that emphasized specific populations (e.g., *Society for Adolescent Health and Medicine*, $n = 16$) or specific health areas (e.g., *Addiction Health Services Research Conference*, $n = 16$).

Advice network

Individual Network Metrics Table 3 displays the individuals with the top 10 highest scores on three individual network measures: in-degree (i.e., popularity), betweenness centrality (i.e., brokerage), and eigenvector centrality (i.e., prestige). Collectively, these individuals account for 49% of all 483 ties in the advice network. We computed a cumulative score, reflecting cumulative rank across all three measures of centrality in the advice network. As shown in Table 3, there is significant overlap across the three network measures and the cumulative score, with many of the same individuals holding top positions with respect to popularity, brokerage, and prestige. Most individuals were, at the time of data collection, affiliated with academic institutions; fewer representatives were from research divisions of integrated delivery systems (e.g., VA, Kaiser Permanente) and government funding agencies (e.g., NIH). To complement information presented in Table 3, and to provide an example, Fig. 1 presents a visualization of the relationships between individuals (i.e., sociogram) of those with the highest in-degree scores (i.e., popularity) in the advice network. Individuals provided written permission to be identified in Table 3 and Fig. 1, respectively.

Global Network Metrics The advice network consisted of 421 nodes (i.e., size), 483 ties, 185 isolates, and density of 0.0027. These metrics indicate that the advice network is very sparse and contains many isolates. The largest connected component of the advice network was comprised of 215 individuals. The average geodesic distance (Wasserman and Faust 1994) or "degrees of separation" between pairs of respondents was 2.60 and the clustering coefficient was 0.32. We compared the average geodesic distance (GD_{ER}) and clustering

Table 2 Top 20 D&I journals and D&I conferences by use or attendance

Journals	Frequency (*N*)		
	Always	Occasionally	Never
1. Implementation Science	194	147	49
2. American Journal of Public Health	58	250	76
3. Administration and Policy in Mental Health and Mental Health Services Research	45	116	215
4. American Journal of Preventive Medicine	42	202	140
5. Translational Behavioral Medicine: Practice, Policy, Research	36	109	217
6. Health Affairs	34	115	111
7. Psychiatric Services	31	76	216
8. Institute of Medicine Reports	30	92	53
9. Medical Care	27	150	199
10. Journal of Public Health Management and Practice	24	133	221
11. Health Services Research	23	119	118
12. Prevention Science	23	102	200
13. American Journal of Community Psychology	22	145	204
14. BMJ Quality and Safety	20	92	209
15. New England Journal of Medicine	18	95	65
16. Preventing Chronic Disease	15	42	135
17. The Joint Commission Journal on Quality and Public Safety	14	103	255
18. Journal of American Medical Association	13	56	14
19. Journal of Public Health	12	83	144
20. Journal of Consulting and Clinical Psychology	12	42	112

Conferences	Attended in past 3 years (*N*)
1. NIH D&I in Health Conference	207
2. APHA Annual Meeting	97
3. VA Quality Enhancement Research Initiative	80
4. AcademyHealth Annual Research Meeting	76
5. Global Implementation Conference	64
6. Society for Behavioral Medicine	54
7. NIMH Conference on Mental Health Services Research	42
8. Society for Prevention Research	33
9. APA Annual Convention	26
10. American Evaluation Association	25
11. Annual Meetings of the Prevention Research Centers Network	25
12. Seattle Implementation Research Conference	23
13. IHI's National Forum on Quality Improvement for Health Care	22
14. HMO Research Network Annual Conference	20
15. NIH Training Institute for D&I Research in Health[a]	20
16. Global Symposium on Health Systems Research	18
17. Association of Behavioral and Cognitive Therapies (D&I Science Special Interest Group)	16
18. Addiction Health Services Research Conference	16

Table 2 continued

Conferences	Attended in past 3 years (*N*)
19. Society for Adolescent Health and Medicine	16
20. Academy of Management	16

Top 20 journals out of 57 total. Item: How frequently do you find articles about D&I that are of interest to you and your work in the following journals? Response option: Select all that apply. Top 20 conferences out of 67 total. Item: In the past 3 years, did you attend any of the following conferences specifically related to D&I? Response option: Select all that apply. Participants had the option of adding journals and conferences not otherwise listed

[a] Technically, this is a training program, not a conference

coefficient of the advice network with the average geodesic distance and the clustering coefficient of a random Erdos–Renyi (C_{ER}) network (Barabási and Albert 1999) with identical size and tie density. The average geodesic distance was much smaller than in a random network ($GD_{ER} = 9.1841$), while the clustering of the advice network was much higher than in a random network ($C_{ER} = 0.0055$). Taken together, both the average geodesic distance and the large clustering coefficient indicate that the advice network has the characteristics of a small world network (Watts and Strogatz 1998; Milgram 1967), where each individual can seek advice from all other individuals through a relatively small number of intermediaries, even though individuals mostly seek advice from a few others who in turn seek advice from each other.

Collaboration network

Individual Network Metrics Table 3 displays the individuals with the top 10 highest scores on the aforementioned three network measures of individual actors: degree (i.e., popularity), betweenness centrality (i.e., brokerage), and eigenvector centrality (i.e., prestige). Collectively, these individuals account for 27% of all 270 ties in the collaboration network. We computed a cumulative score, reflecting cumulative rank across all three measures of centrality in the collaboration network. As shown in Table 3, there is significant overlap of individuals across the three measures and the cumulative score, with many of the same individuals holding multiple roles within the network in terms of popularity, brokerage, and prestige. Overall, most individuals, at time of data collection, were affiliated with academic institutions, with fewer representatives from research divisions of integrated delivery systems (e.g., VA, Kaiser Permanente) and government funding agencies (e.g., NIH). Individuals holding these key positions have primary research interests in both health care and public health. Again, to complement information presented in Table 3, and to provide an example, Fig. 2 presents a visualization of the relationships between individuals (i.e., sociogram) of those with the highest in-degree scores (i.e., popularity) in the collaboration network. Individuals provided written permission to be identified in Table 3 and Fig. 2, respectively.

Global Network Metrics The collaboration network consisted of 421 nodes, 270 ties, 237 isolates, and density of 0.0031 (Wasserman and Faust 1994; Monge and Contractor 2003). Similar to the advice network, the collaboration network was very sparse (i.e., few collaborative relations). The largest connected component consisted of 140 individuals. The average geodesic distance or "degrees of separation" was 4.13 and the clustering

Table 3 Rank of individuals with top 10 scores in advice network and collaboration network

Rank	In-degree (popularity)	Betweenness centrality (brokerage)	Eigenvector centrality (prestige)	Cumulative score
Advice network				
1.	Russ Glasgow	Brian Mittman	Enola Proctor	Brian Mittman
2.	Greg Aarons	Greg Aarons	Russ Glasgow	Enola Proctor
3.	Brian Mittman	Enola Proctor	Ross Brownson	Greg Aarons
4.	Ross Brownson	Laura Damschroder	Brian Mittman	Ross Brownson
5.	Enola Proctor	John Landsverk	Greg Aarons	John Landsverk
6.	Laura Damschroder	Wynne Norton	John Landsverk	Wynne Norton
7.	John Landsverk	Ross Brownson	Rachel Tabak	Laura Damschroder
8.	James Dearing	C. Hendricks Brown	Byron Powell	C. Hendricks Brown
9.	Wynne Norton	Lori Ducharme	Lori Ducharme	Lori Ducharme
10.	C. Hendricks Brown	Byron Powell	Ana Baumann	Byron Powell
Rank	Degree (popularity)	Betweenness centrality (brokerage)	Eigenvector centrality (prestige)	Cumulative score
Collaboration network				
1.	Greg Aarons	Brian Mittman	Russ Glasgow	Brian Mittman
2.	Brian Mittman	Greg Aarons	Brian Mittman	Russ Glasgow
3.	Russ Glasgow	Russ Glasgow	Ross Brownson	Greg Aarons
4.	Ross Brownson	Ross Brownson	Greg Aarons	Ross Brownson
5.	Enola Proctor	Enola Proctor	Enola Proctor	Enola Proctor
6.	James Dearing	Ana Bauman	Ana Baumann	Ana Baumann
7.	Rinad Beidas	Helen Meissner	Helen Meissner	James Dearing
8.	Cynthia Vinson	James Dearing	Cynthia Vinson	Helen Meissner
9.	Bryan Weiner	Cara Lewis	James Dearing	Rinad Beidas
10.	Ana Baumann and Wynne Norton (same score)	Rinad Beidas	Borsika Rabin	Cynthia Vinson and Wynne Norton (same score)

All individuals provided written permission to have their name listed above. Cumulative score is based on cumulative rank across all three measures within each network; actual scores are not presented to maintain confidentiality

coefficient was 0.16. As with the advice network, we compared the average geodesic distance (GD_{ER}) and the clustering coefficient of the collaboration network to the average geodesic distance and clustering coefficient of a random Erdos–Renyi (C_{ER}) network (Barabási and Albert 1999) with identical size and tie density. The average geodesic distance was lower than that of a random network ($GD_{ER} = 11.1686$) and clustering of the collaboration network was much higher than that of a random network ($C_{ER} = 0.0034$), indicating that the collaboration network bears the characteristics of a small world network (Watts and Strogatz 1998; Milgram 1967; Watts 2004) indicating that each individual in the network is connected to all others through a relatively small number of collaboration intermediaries, although many of their collaborations are with individuals who in turn collaborate with one another.

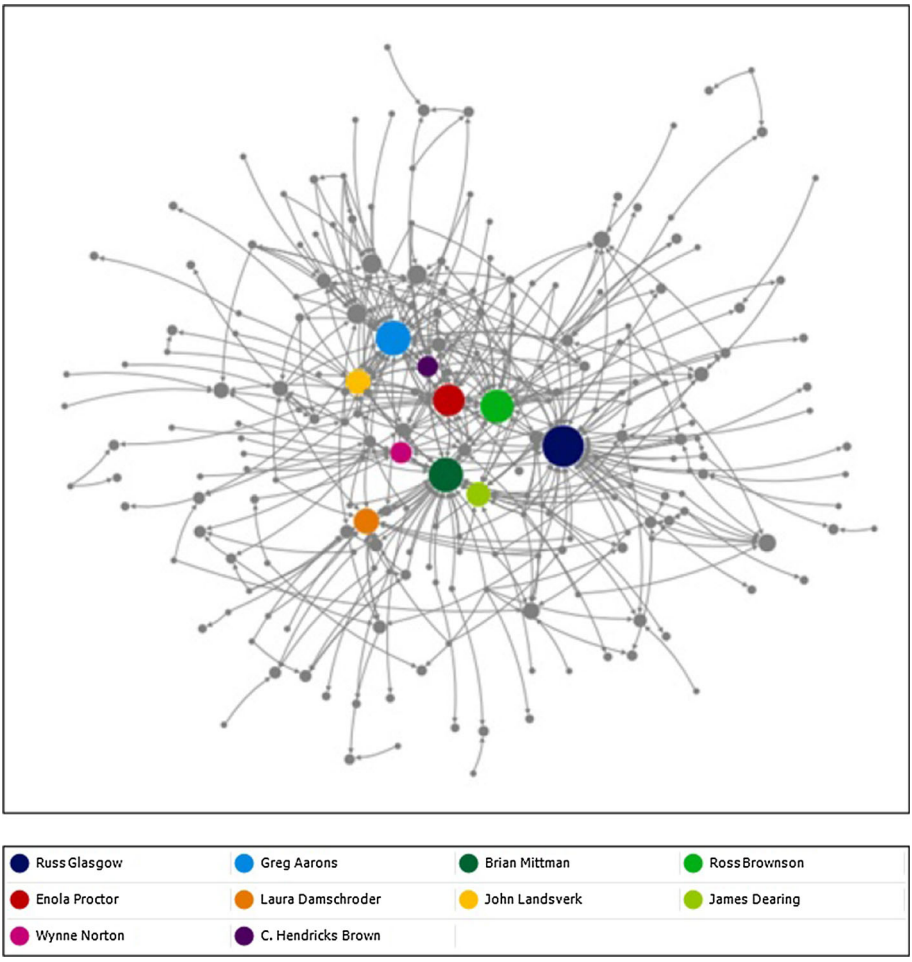

Fig. 1 Sociogram of individuals with the top 10 in-degree scores (popularity) in the advice network. *Note* Top 10 individuals with the highest number of incoming ties from other actors (i.e., highest number of in-degrees) in the advice network are reference by *color* in the legend above ($n = 10$). Node size is proportional to the number of advice links received for named individual. For ease of visualization, we show the largest component in the advice network, comprised of 215 respondents. (Color figure online)

Motivations for collaboration

Table 4 displays count data ('*Select all that apply*') for participants' self-reported motivation for collaboration on D&I activities. They responded to 15 statements representing 8 established theories for building networks (Monge and Contractor 2003). Uncertainty reduction theory, reflected by the statement, '*We have worked together previously*,' received the highest number of counts (211), whereas one of several statements reflecting homophily theory, '*We are of the same gender*,' received the lowest number of counts (9). Statements reflecting theories of preferential attachment (e.g., '*He/she is recognized as a successful researcher'*) and collective action (e.g., '*We have a better chance of success working together'*) also received high counts (206 and 116). Counts for statements

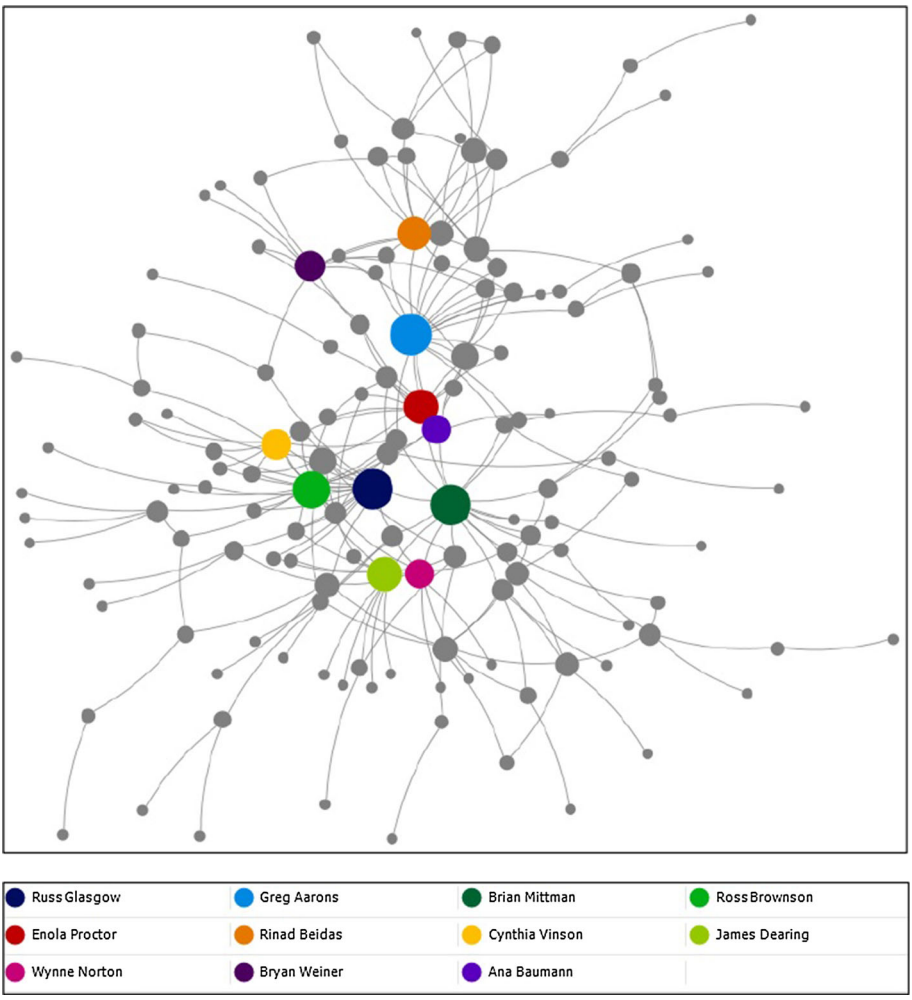

Fig. 2 Sociogram of individuals with the top 10 degree scores (popularity) in the collaboration network. *Note* The top 11 individuals (two had same score) with the highest number of incoming ties from other actors (i.e., highest number of degrees) in the collaboration network are reference by *color* in the legend above. Node size is proportional to the number of collaboration links for named individual. For ease of visualization, we show the largest component in the advice network, comprised of 140 respondents. (Color figure online)

reflecting resource dependency theory were split, with '*I would like to be mentored by him/her*' receiving 126 counts and '*I would like to mentor him/her*' receiving only 17 counts. Statements reflecting trust, homophily, and proximity as motivations for collaboration received the fewest counts.

Researchers' scientific performance in D&I

Researcher Characteristics As shown in Table 5, a total of 295 individuals provided complete data and indicated 'researcher' as their primary professional role. Most researchers were female ($n = 210$, 71%) and White ($n = 235$) with relatively uniform

Table 4 Motivation for collaboration

Count	Item	Theory of motivation
211	We have worked together previously	Uncertainty reduction
206	He/she is recognized as a successful researcher	Preferential attachment
156	He/she is recognized as a good collaborator	Preferential attachment
126	I would like to be mentored by him/her	Resource dependency
116	We have a better chance of success working together	Collective action
100	We are in the same department	Homophily
87	We are friends	Trust
78	We have the same disciplinary background	Homophily
59	We have dissimilar disciplinary backgrounds	Heterophily
57	We are on the same campus	Proximity
33	We are at a similar professional level	Homophily
32	We have friends in common	Trust
17	I would like to mentor him/her	Resource dependency
9	We are of the same gender	Homophily

Data represent responses from 342 participants. Response option: select all that apply

representation from all three age categories (i.e., 39 and younger, 36%; 40–49, 26%; 50 and older, 37%). More than half (64%) reported publishing at least one D&I article within the past 3 years; the majority (67%) reported submitting at least one D&I grant in the past 3 years; and less-than-half (44%) reported receiving funding for at least one D&I grant in the past 3 years.

Predictors of D&I publication

Individual Predictors Model 1 of Table 6 reports individual-level predictors of publishing at least one (vs. none) D&I article in the past 3 years among the sub-sample of 295 researchers. With respect to demographic predictors, we found no effect of age, gender, or race/ethnicity on likelihood of publication, which is important insomuch as these characteristics are fixed and rather immutable to modification. The non-significant relationship between demographic characteristics and publication is consistent with other scientific disciplines: Ceci and Williams (2011), for example, found no evidence of gender bias on scientific publication in math-intensive fields.

Researchers who reported their D&I expertise level as *Intermediate* were significantly more likely to publish at least one (vs. none) D&I article in the past 3 years than researchers who reported their D&I expertise level as *Novice*. This pattern of results was consistent for researchers with *Advanced/Expert* (collapsed) expertise compared to *Novice* expertise, respectively. Researchers who became involved in the field of D&I in 2010 or later were significantly less likely to publish at least one (vs. none) D&I article than those who became involved before 2000.

Individual and Advice Network Predictors Model 2 of Table 6 includes the effect of the advice network on D&I publications. Network status was a significant predictor of D&I publication: researchers with high status (i.e., someone who is sought for advice from the people who are in turn sought for advice from others (Monge and Contractor 2003) had a

Table 5 Characteristics of researchers ($N = 295$)

Variable	N (% of total)
Gender	
Female	210 (71%)
Male	85 (29%)
Race/ethnicity[a]	
White	235
Other[b]	60
Age	
39 or younger	109 (36%)
40–49	77 (26%)
50 or older	109 (37%)
Initial involvement in D&I	
Before 2000	44 (15%)
2000–2009	162 (55%)
2010 or Later	89 (30%)
D&I expertise	
Novice	82 (28%)
Intermediate	144 (49%)
Advanced/expert[c]	69 (23%)
D&I publication(s) in past 3 years[d]	
Yes	188 (64%)
No	107 (32%)
Number of D&I grant(s) submitted in past 3 years	
0	97 (33%)
1	68 (23%)
2	49 (17%)
3	44 (15%)
4 or more (maximum: 10)	37 (13%)
Number of D&I grant(s) funded in past 3 years	
0	164 (56%)
1	72 (24%)
2	32 (11%)
3 or more (maximum: 5)	27 (9%)

[a] Select all that apply response option; overall sample percentages not included

[b] Due to small sample sizes, we collapsed non-white responses (e.g., African-American, Asian, Hispanic) into a single 'Other' category

[c] Due to small sample sizes, we collapsed advanced and expert into a single category

[d] At least one (vs. none) D&I-related publication in past 3 years. D&I = dissemination and implementation. Percentages may not add up to 100% due to 'prefer not to answer' response option (data not shown)

higher probability of publishing at least one D&I article in the past 3 years than those with low status ($\beta = 2.98$, $p \leq 0.01$). The addition of advice network predictors improved model fit above and beyond the individual predictors-only model, $\chi^2 = 6.78$, $p \leq 0.001$ (Wald 1943).

Individual and Collaboration Network Predictors Model 3 of Table 6 includes the effect of the advice network on D&I publications. Network connectedness was a significant predictor of publication: researchers with more collaborators were more likely to publish at least one (vs. none) D&I article than those with fewer collaborators ($\beta = 0.98$, $p \leq 0.01$). Closure was a non-significant predictor of publication: Individuals who collaborate with others who do not collaborate with each other are no more likely to have at least one D&I publication than those who collaborate with others who collaborate among themselves. The

Table 6 Probit regression analyses predicting D&I publication (yes/no) among researchers ($n = 295$)

Variable	Model 1: control	Model 2: advice network	Model 3: collaboration network
Gender (reference category: male)	0.12	0.09	0.10
	(0.18)	(0.19)	(0.18)
Race (reference category: white)	−0.07	−0.08	−0.06
	(0.19)	(0.20)	(0.20)
Age (reference category: 20–29)			
40–49	−0.18	−0.17	−0.14
	(0.21)	(0.21)	(0.21)
50 or older	−0.20	−0.25	−0.19
	(0.21)	(0.22)	(0.21)
Initial involvement in D&I (reference category: before 2000)			
2000–2009	−0.48	−0.44	−0.48
	(0.30)	(0.32)	(0.31)
2010 or Later	−0.64*	-0.60^{+}	−0.66*
	(0.34)	(0.35)	(0.35)
D&I expertise (reference category: novice)			
Intermediate	0.97***	0.94***	0.90***
	(0.21)	(0.22)	(0.22)
Advanced/expert	1.07***	0.83**	0.88***
	(0.28)	(0.29)	(0.29)
Status (advice network)		2.98**	
		(0.11)	
Connectedness (collaboration network)			0.98***
			(0.07)
Closure (collaboration network)			0.01
			(0.48)
Pseudo R^2	0.14***	0.18***	0.17***
χ^2: change in R^2 versus Model 1		6.78***	11.98***

Standardized beta coefficients; Standard errors in parentheses; observations = 295; two-tail model; $^{+}$ $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$, *** $p \leq 0.001$. Coding: 0 = No D&I-related publications in past 3 years; 1 = At least one D&I-related publication in past 3 years. Publications could be co-authored or first-authored

addition of collaboration network predictors significantly improved model fit compared to the individual predictors-only model, $\chi^2 = 11.98$, $p \leq 0.001$ (Wald 1943).

Predictors of funded D&I grants

Individual Predictors Models 1a and 1b of Table 7 report on the individual level predictors of number of funded D&I grants and the ratio of the funded to submitted D&I grants. Specifically, *Advanced/Experts* (collapsed) were more likely to have funded grants than *Novices* and, similarly, *Intermediates* were more likely to have funded grants than *Novices*. Importantly, this suggests that the field is funding not only *Advanced/Expert* researchers

Table 7 Ordinary least squares regression analyses predicting funded D&I grants among researchers ($n = 295$)

Variable	Number of funded D&I grants			Funded-to-submitted ratio of D&I grants		
	Model 1a: control	Model 2a: advice network	Model 3a: collaboration network	Model 1b: control	Model 2b: advice network	Model 3b: collaboration network
Gender (ref. categ. male)	−0.06	−0.05	−0.05	−0.07	−0.06	−0.06
	(0.09)	(0.09)	(0.09)	(0.05)	(0.05)	(0.05)
Race (ref. categ. white)	−0.03	−0.03	−0.02	−0.07	−0.07	−0.06
	(0.10)	(0.10)	(0.10)	(0.06)	(0.06)	(0.06)
Age (ref. categ. 20–29)						
40–49	0.01	0.02	0.01	0.01	0.01	−0.01
	(0.10)	(0.10)	(0.10)	(0.06)	(0.06)	(0.06)
50 or older	0.03	0.03	0.03	0.00	0.00	0.01
	(0.10)	(0.10)	(0.10)	(0.06)	(0.06)	(0.06)
Initial involvement in D&I (ref. categ. before 2000)						
2000–2009	−0.07	−0.04	−0.05	−0.08	−0.06	−0.06
	(0.15)	(0.15)	(0.15)	(0.08)	(0.08)	(0.08)
2010 or later	−0.02	0.00	−0.01	−0.05	−0.03	−0.03
	(0.16)	(0.16)	(0.16)	(0.09)	(0.09)	(0.09)
Expertise (ref. categ. Novice)						
Intermediate	0.02	0.03	0.03	0.24**	0.24**	0.25**
	(0.09)	(0.09)	(0.09)	(0.06)	(0.06)	(0.06)
Advanced/expert	0.11*	0.09^{+}	0.10^{+}	0.25**	0.23**	0.25**
	(0.13)	(0.13)	(0.14)	(0.07)	(0.07)	(0.08)
Number of submitted D&I grants	0.73***	0.70***	0.70***			
	(0.02)	(0.03)	(0.03)			
Status (advice network)		0.11*			0.09*	
		(0.01)			(0.00)	

Table 7 continued

Variable	Number of funded D&I grants			Funded-to-submitted ratio of D&I grants		
	Model 1a: control	Model 2a: advice network	Model 3a: collaboration network	Model 1b: control	Model 2b: advice network	Model 3b: collaboration network
Connectedness (collaboration network)			0.13**			0.13**
			(0.02)			(0.01)
Closure (collaboration network)			−0.10***			−0.16***
			(0.15)			(0.06)
Adjusted R^2	0.62***	0.63***	0.63***	0.06***	0.06***	0.08***
R^2	0.63***	0.64***	0.65***	0.08***	0.09***	0.11***
χ^2: Change in R^2 versus Model 1		8.03***	4.83*		14.18***	4.35*

Standardized beta coefficients. Standard errors in parentheses. Observations = 295. Two-tail model; $^{+}$ $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$, *** $p \leq 0.001$

but *Intermediate* researchers, as well. Consistent with the pattern of results for D&I publication, demographic characteristics were non-significant predictors of number of funded grants and ratio of funded-to-submitted grants. Not surprisingly, the number of submitted grants was a strong, significant predictor of having a grant funded.

Individual and Advice Network Predictors Models 2a and 2b of Table 7 include the effects of the advice network on number of funded grants and the ratio of funded to submitted grants. Individuals with high status (i.e., someone who is sought for advice from the people who are in turn sought for advice from other people (Monge and Contractor 2003) had a higher likelihood of having a funded D&I grant (Model 2a: $\beta = 0.11$, $p \leq 0.05$; Model 2a: $\beta = 0.09$, $p \leq 0.05$) than those with low status. The addition of the advice network predictors improved model fit for both number of funded grants and ratio of funded-to-submitted grants compared to the individual predictors-only model, Model 2a: $\chi^2 = 8.03$, $p \leq 0.001$ and Model 2b: $\chi^2 = 14.18$, $p \leq 0.001$ (Wald 1943).

Individual and Collaboration Network Predictors Models 3a and 3b of Table 7 show that individuals with more collaborators were more likely to have a funded D&I grant than those with fewer collaborators (Model 3a/b: $\beta = 0.13$, $p \leq 0.01$). In addition, the lower the closure (or higher brokerage) in the collaboration network, the greater the likelihood of a researcher having a funded D&I grant (Model 3a: $\beta = -0.10$, $p \leq 0.001$; Model 3b: $\beta = -0.16$, $p \leq 0.001$). In other words, researchers whose collaborators do not collaborate with each other are more successful in securing grant funding than those whose collaborators do collaborate with each other. This suggests that individuals who collaborate with those who do not collaborate with each other are uniquely positioned to combine insights and expertise from their collaborators to generate novel ideas that are more likely to lead to funded grants. The addition of the collaboration network predictors significantly improved model fit compared to the individual predictors-only model, Model 3a: $\chi^2 = 4.83$, $p \leq 0.05$ and Model 3b: $\chi^2 = 4.35$, $p \leq 0.05$ (Wald 1943).

Discussion

The overall objective of the present study was to characterize the D&I community. A distinctive feature of the study was to utilize self-report surveys to characterize the D&I community. Specifically, we mapped (1) the demographics of the community, (2) the intensity and diversity of intellectual resources—journals and conferences—with which they engaged, (3) the advice and collaboration networks within the community, (4) individuals' motivations in selecting their collaborators, and (5) the extent to which individuals' positions in the advice and collaboration network explained the likelihood of them publishing or being awarded grants above and beyond what is explained by individuals' demographic characteristics. The 421 participants reflected a range of demographic characteristics, years of involvement in D&I, and expertise in D&I. The participants reported active engagement with a wide variety of journals and conferences, although there was one journal (*Implementation Science*) and one conference (*NIH D&I in Health Conference*) that dominated. A select number of individuals held key positions within and across the advice and collaboration networks, similar to the relatively select group of influential authors in the fields of knowledge utilization (Estabrooks et al. 2008) and research utilization in nursing (Estabrooks et al. 2004). Like many other social networks, the advice and the collaboration networks in the D&I community exhibited small world

characteristics—with individuals connecting with others who are often connected to each other, but a handful of network connections with others enabling them to be just a few degrees of separation from most others in the network. Unlike many other social networks, the networks in the D&I community had a substantial number of isolates ($n = 185$ in advice network; $n = 237$ in collaboration network)—a potential source of concern with actionable implications in terms of community building efforts discussed later.

The study also revealed important insights about researchers' motivation for selecting collaboration partners. The most important priority (reported by 50%) was for researchers to select collaborators with whom they had previously worked. This reflects researchers' motivation to reduce uncertainty in the collaboration. Prior research has demonstrated that researchers are more likely to submit grant proposals with those with whom they have previously worked and that these proposals are more likely to be funded (Lungeanu et al. 2014). The second (reported by 48%) and third (37%) most important priorities were for researchers to seek collaborators who are recognized as successful researchers and good collaborators. These motivations are consistent with the phenomena of the so-called "Mathew effect" first introduced by Merton (1968). Merton argued that, in science, and indeed more generally in society, individuals had a preference for "attaching" to those who are already well connected thereby making the rich (highly connected collaborators) even richer. Seeking mentoring was also an important motivation (reported by 30%) for selecting a collaborator. While this demonstrates a substantial interest in being mentored, only 4% reported mentoring someone as a motivation for selecting a collaborator. This asymmetry is potentially problematic for nurturing the next generation of scholars because it shows an imbalance between those requiring (intellectual) resources and those willing to share those resources. In addition, approximately 28% of respondents reported that they chose collaborators based on the logic of collective action—that together they had a better chance of success than working alone.

It is noteworthy that the top 5 motivations are all strategically geared toward improving the odds of scientific advancement. These contrast with 7 out of the remaining 9 motivations which are not strategic but reflect human proclivities for selecting collaborators based on homophily (same disciplinary background, same department, same gender, same professional level), proximity (same campus), and trust (friends, or friends in common). While these motivations reflect human tendencies, they are not always precursors of success in interdisciplinary research contexts (such as D&I) that benefit from diversity (Wuchty et al. 2007). It is promising, however, that a small number of respondents (14%) were consciously being strategic about selecting collaborators with different disciplinary backgrounds.

Our analysis also revealed important associations between individuals' positions in the collaboration and advice network and their D&I publications and grant activity. Regression analyses identified individual- and network-level predictors of scientific performance—D&I publication and funded D&I grants—based on a sub-sample of 295 researchers. Results were relatively consistent across both outcomes: researchers with greater D&I expertise, higher status, and higher connectedness were more likely to publish and have funded grants than those with lower expertise, lower status, and lower connectedness. Importantly, demographic characteristics were non-significant predictors of either D&I publication or D&I funded grants. A few predictors were significant for D&I publication but not D&I funded grants. Specifically, researchers who initiated involvement in the field of D&I in the year 2010 or later were significantly less likely to publish than those who initiated involvement before 2010. Researchers who collaborate with others who do not collaborate with each other were less likely to have funded grants than those who

collaborate with others who collaborate among themselves. The strongest predictor of D&I funded grants, however, was number of grant submissions, which accounted for approximately 55% of the variance in funded grants, providing support for the adage that persistence is key to grant success.

This study provides a starting point for understanding the diverse landscape of individuals involved in the field of D&I. Identification of sources of information for D&I research provides a data-driven guide for those new to the field, as well as an opportunity for those already involved to expand or increase their knowledge base. Network analyses identify important leaders in D&I as well as robust collaborative partnerships, and should be instrumental in guiding efforts to advance the field, which may include network-based interventions (Valente 2012). For example, node-addition interventions (Valente 2012), whereby new individuals are added to a network, could be used to bridge one group with another or to enhance reach by establishing ties with isolates. Rewiring interventions (Valente 2012) may be used to connect individuals with complementary interests (e.g., qualitative researcher with quantitative researcher; cancer researcher with public health researcher) or unique needs (e.g., junior researcher with senior expert); induction interventions (Valente 2012) could be leveraged to quickly and efficiently distribute important and timely information throughout the network. The degree to which network-based interventions could enhance or accelerate the field of D&I depends on many factors, of course, but may offer an effective, evidence-based approach toward accelerated growth, improved productivity, and increased impact. Finally, longitudinal studies should explore how the field of D&I evolves, adapts, and advances over time (see, for example, Lungeanu and Contractor (2015) for a longitudinal study mapping the emergence of the oncofertility field) (Lungeanu and Contractor 2015). Investigation into characteristics of highly-productive interdisciplinary teams within the field should yield important insight and practical application as well as contributing to the rich literature on team science (Falk-Krzesinski et al. 2010).

Several limitations should be noted. The sample of subscribers to the *e-Newsletter* may not fully represent the population of those engaged in the field of D&I in health, and those involved in the field may have changed since data collection in 2012. Despite potential selection bias, however, and the time period during which these data were collected, the results presented herein provide a snapshot of activities in the relatively early development of the D&I field, and include a sample size ($N = 421$) and response rate (30.75%) comparable to other studies of emerging scientific disciplines (Merrill et al. 2011). We purposely used self-report to assess network-level characteristics to capture a broader and more nuanced understanding of the advice and collaboration relationships rather than the more limited interpretation offered by bibliometric analysis. Future research should compare results presented herein with bibliometric analyses of co-authorship and/or co-funding. The degree to which the advice and/or collaboration networks remain stable over time is unknown; longitudinal assessments and complementary (e.g., bibliometric) analytic methods are needed to understand how relationships among individuals in the field of D&I change over time and, importantly, to assess—and potentially improve—their collective impact on the field. Network-based interventions to improve the D&I field would need to be tailored based on any changes that may have occurred in the structure and connectivity of the network from data collection to present day.

Conclusions

Many individuals are actively engaged in the emerging scientific discipline of D&I in health, utilizing a variety of resources (e.g., journals, conferences) and social networks (e.g., advice, collaboration) to advance the field. When seeking D&I advice and/or D&I collaborations, participants have relied on a relatively small and select group of individuals, many of whom hold multiple key positions within and across both networks. The most important motivations for selecting collaborators were strategically aligned with advancing the science (i.e., prior collaborators, strong reputation, good collaborators, and mentoring) rather than relying on human proclivities for homophily, proximity, and friendship. There was a stark imbalance, however, between the large number of respondents who reported receiving mentoring as a motivation for choosing collaborators and the small number of respondents who reported offering mentoring as a motivation for selecting collaborators. Finally, individuals' positions in the advice and collaboration networks were significant predictors of D&I publication and D&I funded grants above and beyond what was explained by demographic variables. Additional research is needed to fully capture, understand, and assess individuals' involvement in D&I research, including longitudinal assessments to examine changes since time of data collection and prospectively as the field changes in the future, to inform the selection and use of tailored network interventions to facilitate progress and impact.

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Authors' contribution WEN participated in study development, study design, coordination of data collection, data interpretation, and manuscript writing and editing. AL participated in data analysis, data interpretation, and manuscript writing and editing. DAC participated in data interpretation and manuscript writing and editing. NSC participated in study development, study design, coordination of data collection, data interpretation, and manuscript writing and editing.**Compliance with ethical standards**

Conflict of interest NSC is the co-founder and Chairman of *Syndio.* WEN, AL and DAC have no competing interests.

Ethical approval The Institutional Review Boards at the University of Alabama at Birmingham and Northwestern University reviewed and approved the study under exempt status.

Informed consent Individuals listed in Table 3 provided written consent to be named in the manuscript.

Availability of data and material The datasets generated during and/or analyzed during the current study are not publicly available to maintain privacy and confidentiality associated with social network data.

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