Network approaches and interventions in healthcare settings: A systematic scoping review

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Abstract

The growing interest in networks of interactions is sustained by the conviction that they can be leveraged to improve the quality and efficiency of healthcare delivery systems. Evidence in support of this conviction, however, is mostly based on descriptive studies. Systematic evaluation of the outcomes of network interventions in healthcare settings is still wanting. Despite the proliferation of studies based on Social Network Analysis (SNA) tools and techniques, we still know little about how intervention programs aimed at altering existing patterns of social interaction among healthcare providers affect the quality of service delivery. We update and extend prior reviews by providing a comprehensive assessment of available evidence.

Methods and findings

We searched eight databases to identify papers using SNA in healthcare settings published between 1st January 2010 and 1st May 2022. We followed Chambers et al.'s [1] approach, using a Preferred Reporting Items for Systematic reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR) checklist. We distinguished between studies relying on SNA as part of an intervention program, and studies using SNA for descriptive purposes only. We further distinguished studies recommending a possible SNA-based intervention. We restricted our focus on SNA performed on networks among healthcare professionals (e.g., doctors, nurses, etc.) in any healthcare setting (e.g., hospitals, primary care, etc.). Our final review included 102 papers. The majority of the papers used SNA for descriptive purposes only. Only four studies adopted SNA as an intervention tool, and measured outcome variables.

Conclusions

We found little evidence for SNA-based intervention programs in healthcare settings. We discuss the reasons and challenges, and identify the main component elements of a network intervention plan. Future research should seek to evaluate the long-term role of SNA in changing practices, policies and behaviors, and provide evidence of how these changes affect patients and the quality of service delivery.

Keywords Social Network Analysis; Network intervention; Healthcare professionals; Healthcare settings

Introduction

It is widely recognized that there is a gap between best achievable healthcare outcomes and those that are actually delivered, even in the best funded systems, suggesting that more is required than simply increasing available resources [2-3]. Improving healthcare outcomes requires changes in frontline clinical practice, which in turn involves the ability to disseminate information across diverse teams, and to engender alignment of multiple groups.

The diffusion of practices and behaviors within any healthcare setting may be usefully framed as a network problem involving multiple individuals and the way they relate and interact with one another. Leaders aiming to improve healthcare outcomes would benefit from understanding how team members interact, and how interactions may be leveraged to optimize the adoption and diffusion of new practices. Information about patterns of interaction can be obtained using Social Network Analysis (SNA). SNA provides a set of tools and techniques used to investigate structural characteristics of networks [4], and understand how a broad range of behaviors may be triggered by social interaction [5]. SNA generates three main types of outputs. The first is a visual representation of networks structures, or network graphs. The second is a set of metrics providing quantitative information on properties of networks, such as density, or properties of individuals, such as centrality. The third type of output is produced by statistical models for network data, such as models for the analysis of longitudinal networks [6].

SNA outputs can be used to inform the design, implementation and monitoring of behavioral change programs, policies and practices [5,7]. A network intervention can be defined as a structured process using social networks to accelerate behavior change or improve organizational performance [8]. Social networks are channels for information diffusion and interpersonal influence. Hence, changing the wiring of an existing social network may determine changes in how behaviors, ideas and practices spread in a social group.

Valente [8] proposed a taxonomy of four types of network intervention strategies: i) ‘Individuals’, based upon the identification of individuals with certain network characteristics who are recruited to act as change proponents; ii) ‘Segmentation’, involving the identification of subgroups in a network on which to focus behavioral change; iii) ‘Alteration’, whereby an existing network is changed by adding or removing ties or nodes in order to alter patterns of interaction and diffusion, and finally iv) ‘Induction’, whereby peer-to-peer interactions are encouraged through, for example, the use of meetings or training events bringing previously unconnected people together.

While a large body of research is available that relies on SNA to examine networks of health professionals in healthcare settings, much of this research has been descriptive, with limited reporting of the relationship between network interventions and clinical or organizational outcomes. This is confirmed by recent systematic reviews. For example, Chambers et al.’s [1] systematic scoping review of SNA-based studies in healthcare settings found very little evidence of the use of SNA as part of an intervention. Cunningham et al.’s [9] review (1995-2009) included 40 eligible studies. Only one described an SNA-based intervention using survey data to identify opinion leaders, but did not measure its impact. Bae et al.’s [10] systematic review included 28 eligible studies (up to 2013), none of which reported on outcomes of SNA-based interventions. A recent umbrella review by Hu et al. [11] included 13 reviews between 2010 and 2019 and demonstrated a wide applicability of SNA to study health professional networks. Of the 330 papers included in the reviews, only one reported on a network intervention.

The aim of the present review is threefold. First, provide an update of prior reviews by searching for papers using SNA to investigate networks of healthcare professionals in healthcare settings. Second, identify research reporting about network-based interventions and their outcomes. Third, identify the component elements and discuss the main challenges of a network intervention strategy to call attention on its potential in healthcare settings. The primary research question that this review seeks to address is what evidence is available on the adoption of network interventions and evaluation of their effect on care processes and outcomes.

Methods

Protocol

The literature review was undertaken in accordance with the protocol (S1 File) followed by Chambers' et al. in their 2012 review [1]. We used the Preferred Reporting Items for Systematic reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR) statement and guidelines (S2 File) [12].

Information sources and search strategy

The literature search focused on identifying studies performing SNA on networks of healthcare professionals in healthcare settings. We used the same search strategy, inclusion and exclusion criteria and keywords as those used by Chambers et al [1]. We performed a systematic electronic database search of OVID MEDLINE (R) ALL first, using free text terms, synonyms and subject headings associated with social networks and the methods used to investigate them including 'sociometrics', 'sociograms' and 'sociomaps'. We also used words associated with

SNA software, such as NetDraw and UCINET. Finally, the search strategy included the subject headings inter-professional relations, inter-disciplinary communication and physician-nurse relationships. The search strategy was later adapted for other databases in our search. Specifically, for the period 1^{st} January 2010 to 1^{st} May 2022, we searched the following databases: OVID MEDLINE (R) ALL**,** EMBASE Classic+EMBASE, APA PsycINFO, Health Management Information Consortium (HMIC), the Cochrane Library (Cochrane Database of Systematic Reviews, Cochrane Protocols and Cochrane Central Register of Controlled Trials), CINAHL Plus, Business Source Ultimate, Social Science Citation Index (SSCI) and Conference Proceedings Citation Index - Social Science & Humanities (CPCI-SSH) databases. Reference lists of relevant reviews and studies were searched, as was the website of the International Network for Social Network analysis (www.insna.org) and its linked sites. The index of contents of the Social Networks journal was also searched. The online search was run on 5^{th} January 2021 and later updated on 1^{st} May 2022 to include papers published up to this date. The search strategy had no study design filters or restrictions to language as long as the paper could be found in English. Records were managed within a Mendeley library.

Eligibility criteria

The review included studies undertaken in any healthcare setting that reported the results of an SNA performed on networks among healthcare professionals (e.g., doctors, nurses, etc.) and other individuals involved in their professional networks (e.g., management, administrative support etc.). Examples of these networks include discussion networks, advice and knowledge sharing, and working on projects together. The healthcare setting was not restricted to a single geographical or organizational location, and could include wider interpersonal networks, such as the Parkinson network [13]. Veterinary or dental professionals were not included. Studies of networks linking organizations, rather than individuals, were excluded. We excluded studies where network relations were defined solely by patient sharing, as this predicts person-to-person communication only in minority of instances [14].

We built upon Chambers et al.'s [1] classification method. We divided papers into three groups, which we termed level 1 to 3. Level 1 included studies reporting on the impact of an SNA-based intervention. Level 2 included studies describing existing social networks among healthcare professionals without reporting any follow-up action. Level 3 included descriptive studies that went on to suggest an SNA-based intervention intended to affect outcomes and behaviors. We added this additional category to shed light on the significant number of papers acknowledging the value of using SNA to inform the design of intervention plans, and the benefits associated with it.

Study selection and data extraction

Two Authors independently screened studies by title and disregarded those that they agreed to exclude. Studies where there was agreement for inclusion were independently screened by abstract by three Authors. Studies that appeared to meet the review inclusion criteria were forwarded to full-text evaluation and data extraction. The Cochrane EPOC (Effective Practice and Organisation of Care) Group criteria were used to assess the risk of bias by two Authors. Disagreements were discussed with a third Author.

Results

The search returned 31,2867 unique papers, of which 102 met the eligibility criteria. Ten of these [15–24] were also included in Chambers et al.' s [1] review due to a crossover of search periods. We excluded these papers. The PRISMA diagram in Fig 1 below outlines the study selection process, and S1 Table outlines the number of records identified by database with a comparison to Chambers et al.'s [1] review. The comparison seems to suggest an increased use of social network approaches in healthcare studies over the past few years.

Fig 1. Flow diagram of study selection process

Four included studies met the level-1 [13,25–27], 74 the level-2 [15–17,19–21,23,28–94], and 24 the level-3 [18,22,24,95–115] criteria.

Of the 102 papers, one third (n=33) was conducted in the USA, 22 in Europe (excluding UK), 16 in low- and middle-income countries (LMIC), 11 in Australia, eight in the UK, seven in Canada, two in Japan, two in China and one in Malaysia. The Netherlands and Italy produced the largest number of papers in Europe. Compared to previous reviews mentioned earlier, we found an increased number of studies conducted in LMIC. The largest number of studies (n=59) had participants from multidisciplinary teams, and were conducted in secondary care settings (n=64). The number of participants ranged from 10 [71] to 16,171 [66]. The largest number of studies used surveys/questionnaires (n=57), followed by direct observations (n=7), mixed methods (n=13), process logs or other administrative data (n=9), interviews (n=7), online platforms or forums (n=5), and interaction data collected through sensors (n=4).

We summarized the types of ties examined in the included papers into 10 categories to standardize the language (see S2 Table). We also grouped network measures into 36 categories (see S3 Table). These measures were used across studies to describe or analyze networks at the individual, dyadic, group, and whole network levels. We also created a distinct category for those papers performing only statistical analysis of network data, such as Exponential Random Graph Models (ERGMs), Multiple Quadratic Assignment Procedure (MQAP), and Stochastic

Actor Oriented Models (SAOMs). Network visualization was included as a distinct category when it was the only social network method used.

Level-1 studies

Table 1 below includes the level-1 studies, followed by a descriptive summary.

Table 1. The level-1 studies.

Ref	Country	Participants	Setting	Data collection	Type of tie	Network measure(s)	Key network findings	Network intervention	Network strategy	Recommendations
Benton 2015 [26]	Scotland, UK	46 Nurse leaders	Secondary and community care	Survey	Communication	Density; average path length; network diameter	Information exchange network was mapped before and after an intervention bringing unconnected nurse leaders together to work on projects. Six months after there was an increase in network density and a reduction in average path length and more ties spanning different areas of work. Participants with low initial connectedness improved their number of ties. Connectedness and closeness improved considerably for those doing projects but not for individuals not involved in projects.	Results of SNA are fed back to participants. A subgroup of participants was then allocated to projects based on their interest in topics, and their low level of pre-existing connection. The projects required participants to communicate and work together to agree on actions to strengthen organizational strategy.	Alteration and induction	Use SNA followed by visual feedback to staff to stimulate positive change in the network. Bring disparate staff together in project teams to facilitate a sustained increase in connectiveness. Include staff with low baseline connectiveness.
Van de Eijk 2015 [13]	Netherlands	101 Multidisciplinary healthcare professionals involved with Parkinson care	Secondary and primary	Questionnaire and interview	Knowing each other; professional contacts	Number of connections; density; reciprocity	Participants completed a survey at baseline and one year after the training. Connections increased substantially in both networks from baseline to year one. Positive changes being associated with a central role of neurologists and nurse specialists committed to	Multidisciplinary professionals received training in technical and discipline-specific aspects of care, and in communication. Participants are granted access to an online community. There were semi-annual meetings and an annual national conference.	Induction	Provide shared training for multidisciplinary healthcare professionals treating a common disease. Invite participants to be involved in an online community. This may result in increased numbers of connections.

							multidisciplinary care. Perceived team performance did not change.			
Hurtado 2020 [25]	USA	38 (pre) and 55 (post) nurses and nursing assistants	Community hospital	Survey	Advice	7 Network centrality measures	Deployment of champions who had received technical and leadership training was associated with an increase in equipment use, safety compliance and incident reporting. There was a reduction in injuries to staff which was significantly different from 2 control sites.	SNA used to identify influencers in the area of safe patient handling. The top quintile nominations were invited to be champions. They were trained in technical aspects of patient handling and team leadership. They also participated in a number of quality improvement meetings.	Individuals	Use surveys to identify individuals who are already seen as ‘go to’ people for a particular topic. Identify champions, make them visible, and provide training in both technical skills and knowledge, and leadership. Maintain connection with champions through regular meetings.
Lee 2019 [27]	Malaysia	111 Health care workers	Secondary	Questionnaire	Communication	Geodesic distance; density; reciprocity; degree; closeness; betweenness	Hand hygiene compliance improved by a similarly degree in both peer and manager nominated champion arms. There was an improvement in hand hygiene practice and a preference for top-down leadership structure.	In one study arm staff nominated and ranked peers to become change agents. In the second arm, managers selected champions. Change agents and champions promoted hand hygiene in their local workplace.	Individuals	In order to change workplace behavior, select and train local champions; peer nominated or manager nominated champions have similar impact.

The four level-1 studies report on the results of SNA as part of an intervention, which we classified according to Valente [8]. Benton et al. [26] employed ‘alteration’ and ‘induction’ strategies by using shared project work to form new connections and increase interactions among network members. Van de Eijk et al. [13] employed ‘induction’ through training events. The remaining two studies [25,27] focused on ‘individuals’, by using social network methods to identify individuals who would act as champions. The impacts reported in the papers included structural network changes as well as changes in working practices and, in one study, staff safety outcomes. None of the studies reported on the impact on patient outcomes. The overall aim of the reported interventions was to improve organizational performance [26], patient care across the Parkinson’s network [13], safe patient manual handling [25], and hand hygiene [27]. All four papers used the information from SNA to improve connectedness within the networks. A summary of the level-1 studies is provided in turn below.

Benton et al.’s [26] research was set in the National Health Service, Scotland. This was a quasi-experimental, pre-post intervention design. Analysis of the communication network of a group of nurse leaders was performed. Forty-six nurse participants from the acute and community setting participated to a baseline survey, which identified 18 participants for the intervention. Participants were selected because SNA data showed they were relatively weakly connected within the network. They were placed into one of three working groups based on their area of expressed expertise or interest. The aim was to influence the existing communication network by encouraging less connected participants to work together. To facilitate this, SNA data from the initial survey was fed back to all participants. The communication network was measured six months after the first data collection. Following involvement in the working groups, the selected 18 individuals showed substantial increase in number of ties. This was evidenced by a rise in connectedness score, which improved from 15.72 to 33.9, and closeness centrality which improved from 8.76 to 13.17. There were also improvement in global network efficiency and density, while the average path length reduced from 1.58 to 1.48. Network visualization showed more connections between professional groups. The Authors suggested that the wider network effects may have been affected by the feedback of the results of the first survey, which made people aware of their own position, and prompted curiosity about how they could change it. It also made people aware of the expertise available in peers. One weakness of the paper is that increase in connectedness among the 18 project participants was based on a survey done six months after the completion of the project groups. Hence, it is unclear whether the impact on network topology would be continued long term.

Van Der Eijk et al. [13] conducted a parallel group, mixed-methods study in the Netherlands. The study aimed to evaluate the Parkinson network, a nationwide organization with regional networks of health professionals. The study involved 101 multidisciplinary healthcare workers involved with Parkinson's care. Participants, who were based in hospital, nursing home or primary care settings, were selected to take part in a program on the basis of their location and 'motivation' (the latter term is not explicitly defined in the paper). They underwent a training course on multidisciplinary aspects of Parkinson's disease, and were given access to a database of expert therapists in their geographical location. There were also semi-annual meetings and an annual conference. Participants completed a survey on network connections and perceived team performance at baseline. One year later, a subsample was interviewed. There was a substantial increase in the number of 'knowing each other' connections from 1,431 to 2,175 ($p < 0.001$) and in 'professional contact' connections from 664 to 891 ($p < 0.001$). Neurologists and nurse specialists had a central position and were very well connected one year after the program implementation. Overall team performance did not change, but satisfaction with multidisciplinary collaboration increased significantly. There were no data on the impact of network characteristics on either patient outcome measures – such as symptom control or patient satisfaction, or process measures – such as rate of provision of evidence-based elements of care.

Hurtado et al. [25] used social network survey data to identify highly influential co-workers who were recruited as local champions in a safe patient handling education program. The Authors reported that previous studies in this context showed variable short- and long-term impact and that this may be due to a lack of proper methods for selecting workers best suited to exert influence. The study was carried out in critical care areas in one US hospital, and used a survey to collect data on advice seeking for safe patient handling. Individuals showing high centrality in the network were chosen as champions and were trained in safe handling. They were identified to other staff through announcements and wearing of ribbons. The results showed an increase in safety incident reporting, correct equipment use and safety compliance, as well as reduction in staff injuries. Individual injury profile was significantly different from that of the two control hospitals in the same system.

Lee et al. [27] performed a parallel group study comparing two strategies to influence a behavior, hand hygiene compliance, through the use of local champions. The strategies were deployed on two similar medical wards. SNA showed there were few ties between the wards, suggesting that cross contamination was unlikely to occur. Staff on both wards were asked to nominate and rank peers in terms of their suitability to be hand hygiene champions. In one study arm, champions were selected on this basis. In the other study arm, managers selected champions without reference to the peer ranking. The champions themselves did not know how they had been selected. Trained observers used a validated approach to measure hand hygiene compliance during the study. Compliance increased substantially, from 48% to 66% in the peer selected champion arm, and from 50% to 65% in the manager selected champion arm. There was no statistical difference between the groups.

Level-2 studies

Table 2 below includes the level-2 studies, followed by a descriptive summary.

Table 2. The level-2 studies.

Ref	Country	Participants	Setting	Data collection	Type of tie	Network measure(s)	Key network findings
Kim 2021 [91]	Korea	222 Nursing students	University	Survey	Personal and social support	Indegree; outdegree; betweenness	A high level of subjective happiness is associated with a strong social network. Students with a high level of subjective happiness showed high network centrality. SNA can be used to improve nursing students' happiness by utilizing team-learning social networks within programs.
Haruta 2021 [90]	Japan	52 Multidisciplinary healthcare workers	Secondary	Questionnaire	Advice	Clustering; density; degree; reciprocity; betweenness	Advice seeking network structures differed by topic areas. Nurses had highest centrality for all areas. The effect of feeding back the findings to healthcare professionals may have helped them to reflect on, and act upon their own networks.
Mukinda 2021 [92]	South Africa	42 Managers and healthcare providers involved with maternal, newborn and child health	Primary and secondary	Questionnaire	Communication; social support	Degree; betweenness; density	Governance structures can support collaborative networks to improve cohesion between multidisciplinary teams by integrating missing links to improve information sharing and strengthen teamwork between frontline providers.
Bertoni 2022 [94]	Brazil	133 Multidisciplinary or intensive care unit workers	Secondary	Questionnaire and interviews	Advice	In-degree; closeness; betweenness	Key players are not the same across the four ability-based networks. Thus, if responding, anticipating, learning, and monitoring are core activities that a resilient system displays, different individuals may take the lead on each of those roles. It is possible to investigate the contribution of individual players to resilience from a system perspective.
Smit 2021 [89]	Netherlands	55 Multidisciplinary healthcare professionals	Primary	Survey	Collaboration	Degree; reciprocity	It is feasible to implement an interprofessional collaboration in practice (IPCP) program. Secondary data on the reporting of network metrics showed an increase in the number of contacts among the program participants. After the program, the program and non-program participants gained more

							collaborative, and diverse inter-professional networks.
Hayward 2021 (93)	Australia	19 Multidisciplinary professionals involved in disability services	Cross sectors	Survey	Advice	Outdegree; indegree; betweenness	Nineteen individuals are identified who occupy positions of either boundary spanning (those linking people and groups) and/or opinion leadership (those that are sought for advice). Boundary spanners meet all criteria while opinion leaders do not.
Durojiaya 2022 [88]	USA	1647 Multidisciplinary pediatric trauma healthcare workers	Secondary	Electronic health records and interviews	Patient sharing	Network graph	Networks dealing with individual trauma cases are different between day and night. Network patterns for collaborative working are different during day versus night shifts.
Tasselli 2015 [85]	Netherlands	118 Hospital professionals (65 nurses and 53 doctors)	Secondary	Survey	Knowledge transfer	Average degree centrality; hierarchy; average betweenness centrality	There are disciplinary cliques for knowledge transfer. Clinical directors facilitate knowledge transfer through their central network position. Junior doctors and nurse managers display both inter-professional and intra-professional centrality positions and are more likely to access valuable knowledge.
Wagter 2012 [61]	Netherlands	108 ICU/MCU staff (senior doctors, nurses, residents and facilitating jobs)	Secondary	Questionnaire	Knowledge sharing	Densities; tie strength; reciprocity	ICU/MCU nurses formed cliques. There are unilaterally directed relations of senior doctors with nurses and patients.
Malik 2014 [35]	Pakistan	48 Primary physicians and 5 district health administrators and line managers	Primary	Interviews and questionnaire	Advice seeking	Network graph	Primary physicians are aware of available expert knowledge, but advice-seeking behavior is dependent upon existence of informal social interaction with the senior specialists.
Patterson 2011 [28]	USA	3 Emergency medical technician teams (EMT) (size of staff: N=41; N=67; N=81)	Secondary	Administrative data	Familiarity (having worked previously together during shifts)	Number of partnerships; means; rates; proportions	On average, an EMT works with 19 different partners over the course of the year and there is significant variation in EMT partner familiarity across agencies. These patterns are considered an indicator of poor emergency medical services outcomes.

Groenen 2017 [55]	Netherlands	214 Healthcare workers from 8 different professions	Secondary and community	Questionnaire	Patient-related contacts	Density; centrality	Almost all professionals in the network can reach other professionals in two steps. Only community-based midwives have connections with all other groups of professionals and represent 51% of all measured connections. The youth health doctors and nurses are mostly positioned on the edge, and are less connected. Obstetricians and community midwives have the highest score for betweenness centrality.
Yuce 2014 [59]	Netherlands	394 Hospital physicians	Secondary	Questionnaire	Advice	Density; average degree centrality	Advice seeking networks among doctors differ for medical and IT related issues. Trainees are just as likely to approach faculty on medical issues as peers, but more likely to approach peers on IT issues. Faculties go to peers for advice in medical practice, but not to trainees for technology-related advice due to the mentor system. Opinion leaders are different for the two domains.
Sibbald 2013 [50]	Canada	6 Multidisciplinary healthcare teams from 2 primary health care team (PHCT) Practices	Primary	Questionnaire and interviews	Information exchange	Density; indegree	Respondents in the sample of PHCTs generally provide research information to only a few individuals on their teams and, overall, only a few individuals are providing the information. Key players in the knowledge uptake and dissemination process are residents, senior physicians, and nurse practitioners.
Benham-Hutchins 2010 [20]	USA	25 Hospital staff and hand-overs (11 to 20 providers over 5 handoffs)	Secondary	Observation Snowball sampling	Communication	Betweenness; closeness; eigenvector; betweenness centralization; hierarchy	Each handoff network exhibits unique communication patterns and coordination. Most participants prefer verbal communication.
Burt 2012 [42]	USA	25 Hospital physicians at quality improvement sites	Secondary	Survey	Different types of ties and name generator questions	Comparison of name generators	Some physicians maintain a social network organized around a specific colleague who perform multiple roles, while others maintain highly differentiated networks. A set of 5 of the 8 name generators used is needed to distinguish the networks of these physicians. Multiple survey questions are needed to

							elucidate networks of knowledge sharing among physicians.
Shokoohi 2013 [73]	Iran	140 Students (70 clerks, 45 interns and 25 residents) in an educational hospital	Secondary	Questionnaire	Knowledge transfer	Density; indegree; outdegree; reciprocity	Residents are consulted with almost as same as attends on diabetic foot ulcers, hence showing a prominent role in knowledge transfer. The density of clerks-residents and interns-residents is higher than clerks-attends and interns-attends. Indegree centralization in attends-related networks is greater than residents-related networks.
Fuller 2012 [38]	Australia	Two case studies of chronic illness service partnerships (42 partnership staff and 19 informants) in 2 Australian sites	Community	Survey	Communication	Degree; betweenness	Participants in both research groups considered that the network survey accurately described the links between workers related to the exchange of clinical and cultural information, team care relationships, involvement in service management, planning and policy development. Aboriginal workers have a high number of direct links in the exchange of cultural information – suggesting a role of cultural resource – but have fewer direct links in the exchange of clinical information and team care.
Patterson 2013 [39]	USA	103 Clinicians and non-clinician staff in a multidisciplinary Emergency Department (ED) team	Secondary	Survey	Communication	Density; centralization; indegree	There is wide variation in the magnitude of communication cohesion (density) and concentration of communication between clinicians (centralization) by day/night shift and over time. There is also variation in indegree centrality (a measure of power/influence) by day/night shift and over time.
Venkatesh 2011 [86]	USA	1,120 Hospital physicians and other staff (doctors, paraprofessionals, administrative personnel)	Secondary	Survey	Advice	Degree	Ingroup and outgroup ties play a critical role in influencing e-healthcare system use. Further, such use has a positive effect on a variety of quality-of-care metrics that in turn influence patient satisfaction.
Barth 2015 [53]	UK	Pediatric surgery team in 40 pediatric cardiac surgical procedures	Secondary	Observation	Communication	Degree centralization; density; closeness centralization;	In complex surgical procedures, communication patterns are more decentralized and flatter. In critical transition

						betweenness centralization; reciprocity	phases of the procedure, communication is characterized by higher information sharing and participation.
Tsang 2012 [30]	Taiwan	60 Nurses in a dialysis department of a medical centre	Secondary	Survey	Work-related information exchange	Degree; closeness; betweenness	Organizational citizenship behavior (OCB) increases with centrality in both work and friendship networks. Experienced nurses show high centrality in the work networks. In the friendship network, those with high centrality are not necessarily of higher rank in the organization. OCB induced by social ties is satisfactory. It directly increases work satisfaction and alleviates work stress.
Tavakoli Taba 2016 [64]	Australia	31 Breast imaging radiologists	Secondary	Survey	Professional interaction and knowledge sharing	Degree; density; effective size; efficiency; constraint; hierarchy; mean tie strength	There is a positive relationship between diagnostic performance and degree centrality and network size, but a negative relationship with constraint and hierarchy. Overall, the results suggest that radiologists interacting with a closely knit cluster through multiple primary ties – resulting in higher constraints for them – performed worse than radiologists with effective, less constrained (or non-redundant) contacts.
Walton 2010 [21]	Canada	6 Teams in a pediatric ward (doctors, residents and medical students)	Secondary	Observation and questionnaire	Patterns of team interaction	Betweenness	Three different patterns of verbal interaction are observed. In most cases, the attending physician are most talkative and many students and residents spoke infrequently.
Paul 2014 [32]	USA	33 Primary physicians	Community	Survey	Knowledge sharing	Reciprocity; triadic dependence	A physician influential discussion, and a patient-sharing networks are analyzed. Patterns of influential discussions among physicians exhibit triadic dependence. Reduction in reciprocity due to triadic and other higher-order forms of clustering. Geographically proximal physicians are more likely to share patients.
Tighe 2012 [63]	USA	55 Members of Anesthesiology department and 29 patients	Secondary	Service schedule	Communication	Various measures for size and structure of the network, and information flow are	The network exhibits a relatively low density and clustering coefficient, suggesting a low level of redundancy. The high Krackhardt hierarchy score suggests multiple levels of responsibility and supervision between

						used. Many node-level measures are also used	attending, fellow, and resident anesthesiologists. Despite the relatively small size of the core regional anesthesia and perioperative pain medicine) team, its interactions with a large number of services over multiple geographic locations lead to considerable network complexity.
Hinami 2019 [31]	USA	2280 Prescribers of opioid analgesic	Secondary and community	Prescription claim data	Shared benefactors	K-shell centrality	SNA identifies two small, interconnected prescriber communities of high-volume pain management specialists, and three sparsely connected groups of predominantly low-volume primary or emergency medicine clinicians. The sparsely connected clinicians are a risk factor for uncoordinated opioid prescribing.
Long 2014 [52]	Australia	68 Cancer research networks of hospital-based clinicians and university-based researchers	Secondary	Online Survey	Collaboration	Density; components; External-Internal (E-I) index; clustering coefficient	Geographic proximity and past working relationships have significant effects on the choice of current research collaboration partners. Future intended collaborations include a significant number of weak ties and ties based on other members' reputations.
Dauvrin 2017 [72]	Belgium	575 Healthcare professionals working in inpatient and outpatient services	Secondary	Survey	Professional relationships	Degree	At the dyadic level, no significant associations are found between ego cultural competence and alter cultural competence, except for subjective exposure to intercultural situations. No significant associations between centrality and cultural competence, except for subjective exposure to intercultural situations: The most central healthcare professionals are not more culturally competent than less central health professionals.

Altalib 2019 [37]	USA	66 Epilepsy care facilities and 165 providers	Secondary and primary	Secondary data and interviews	Patient sharing	Degree; betweenness; closeness	Across Veterans Affairs Healthcare System (VA) facilities, neurologists are found to be higher on average node degree, betweenness, and closeness centrality measured followed by mental health professionals, then primary. Providers, across disciplines, have higher centrality measures in Epilepsy Centres of Excellence (ECOE) hubs compared to spoke referral facilities and non-affiliated networks. Facilities had a variety of network configurations.
Stewart 2012 [57]	Thailand	46 Pediatric pain practitioners	Secondary	Online discussion forum	Knowledge sharing	Degree; closeness; betweenness; coreness	The network is dominated by one institution and a single profession. There is also evidence of a varied relationship between reading and posting content to the discussion forum. SNA reveals a network with strong communication patterns and users who are central to facilitating communication. SNA also reveals that there is a strong interprofessional and interregional communication, but a dearth of non-nurse participants are identified as a shortcoming.
Blanchet 2013 [62]	Ghana	12 Ghanaian districts; 53 individuals (hospital managers, nurses and district/regional/national health officers, district education officers, community health volunteers, coordinators)	Secondary	Interviews	Coordination and collaboration	Density; distance; degree; betweenness	The departure of an international organization, caused a big shock to the health system, resulting in a change in relationships and power structures within the network. The system shifts from a centralized and dense hierarchical network, to an enclaved network made up of five sub-networks. The sub-networks are less able to respond to shock, circulate information and knowledge across scales or implement solutions. The network is less resilient, yet it responds better to management's need to access information.
Alexander 2015 [70]	USA	12 Certified nursing assistants and registered nurses	Nursing home	Observation	Communication	Network graph	Direct interaction between nurses is higher in the low IT sophistication home and occur in more centralized locations compared to the high IT sophistication home.

Laapotti 2016 [71]	Finland	10 Healthcare professionals with managerial roles, a chair and a secretary	Secondary	Observation	Interactions between team members	Network graphs	The structure of the interaction network reveals that interactions reflect the organizational roles of the participants, as they are focused on the chair.
Lai 2020 [79]	Taiwan	50 Nurses of surgical wards	Secondary	Questionnaire	Friendship	Network graphs; regression	Perceived usefulness, perceived ease of use, and social influence affect behavioral intention to use cloud sphygmomanometer. Besides, perceived ease of use and social influence positively influence perceived usefulness of cloud sphygmomanometer. Peers are helpful in motivating medical staff to use the cloud sphygmomanometer.
Mascia 2014 [40]	Italy	104 Primary physicians and pediatricians	Primary and Secondary	Questionnaire	Knowledge exchange	Outdegree	The number of relationships with hospital colleagues is associated with use of evidence-based medicine.
Shafiei 2018 [82]	Iran	64 Nurses	Secondary	Interviews	Work-related interactions	Degree; closeness; betweenness; eigenvector	Interactions within a department are strong but those between nurses of different departments are not.
Kawamoto 2020 [76]	Japan	76 Intensive Care Unit (ICU) healthcare professionals (HCP)	Secondary	Wearable sensors	Face-to-face interactions	Degree; betweenness; eigenvector	Wearable sociometric sensor badges show nurses have a pivotal role in communication amongst the ICU HCP.
Cavalcante 2018 [77]	Brazil	3 Healthcare professionals (1 doctor and 2 nurses) and their networks' members (19 people)	Mobile Urgent Care Service	Interviews	Work-related interactions	Size; Density	The networks consist of (mutual) relationships that satisfy the demands and needs of service users in an integrated manner while attempting to respect the knowledge and autonomy of each member. Nevertheless, the networks are characterized by poor collaboration ("star" shape) with few transposition points (bridges). This leads to problems in the performance of tasks and mental suffering at work.
Lazzari 2019 [51]	UK	42 Dementia professionals in 3 teams, and 42 patients with Alzheimer's disease	Secondary	Observation	2-mode networks of professionals by services provided	Degree	All professional roles are involved in the case of patients' biological and sociologic personhood. The nurse is the most central figure in the case of biological personhood.
Currie 2012 [87]	UK	36 Pediatric nephrology multidisciplinary teams	Secondary and community	Survey	Knowledge exchange	Degree; betweenness; brokerage roles; density	Knowledge-brokering roles are influenced by professional hierarchy, particularly in the case of clinical knowledge and even more so with medical knowledge.

Chung 2014 [84]	Australia	107 General Practitioners	Primary	Questionnaire	Advice	Density; inclusiveness; components	Considering the GP-patient encounter as a complex system, the interactions between the GP and their personal network of peers give rise to “aggregate complexity,” which in turn influences the GP’s decisions about patient treatment. GPs in simple profiles (i.e. with low components and interactions) in contrast to those in nonsimple profiles, indicate a higher responsibility for the decisions they make in medical care.
Yuan 2020 [49]	USA	207 Nurses in 6 clinical units in an academic hospital	Secondary	Survey	Advice	Mean peer belief (ego-network analysis)	Although mean beliefs across the entire peer network have no effect on individuals' system use, shared peer beliefs were associated with nurses' increased use of the IT system. Reinforcement by the social network appears to influence whether individuals’ own beliefs translate into system use, providing further empirical support that social networks play an important role in the implementation of health information technology.
Uddin 2013 [69]	Australia	85 Physicians networks	Secondary	Health insurance claim dataset	Collaboration	Density Degree; betweenness centralization Exponential random graph models (ERGMs)	Collaboration structures among physicians affect hospitalization cost and hospital readmission rate.
Benton 2014 [48]	Scotland, UK	27 Senior nurses	Virtual	Survey	Communication	Degree; betweenness; eigenvector; density; average path length; network diameter	The majority of nurse leader who participated in the Global Nursing Leadership Institute 2013 Programme are poorly connected in social media, i.e., they have low indegree and outdegree scores. Existing connections are centered on geographic proximity and participation in regional and global bodies.
Mundt 2015 [54]	USA	155 Primary health care professionals from 31 teams at 6 primary care clinics	Community	Survey	Communication	Density; centralization	Teams with dense interactions are associated with fewer hospital days and lower medical care costs. Conversely, teams with interactions revolving around a few central individuals are associated with increased hospital days and greater costs.

Quinlan 2013 [74]	Canada	49 Nurse Practitioners in primary healthcare teams	Primary	Survey	Knowledge transfer	Within-team reciprocation; within-team degree centrality	Mutual understanding increases from one clinical decision to another in some teams and decreases in others. The new Nurse Practitioners play a crucial role in facilitating mutual understanding and knowledge exchange in the newly created multidisciplinary teams. A well-functioning team has effective intrateam knowledge exchange.
Li 2016 [58]	Netherlands	621 Healthcare Professionals (users) and 723 threads over 40 forums	Virtual	Online discussion forum	2-mode network of forum users by discussion threads	Density; centralization; diameter; average path length; SAOMs	The participation level in the discussion within the online community is low in general. A change of lead contributor results in a change in learning interaction and network structure. Health professionals are reluctant to share knowledge and collaborate in groups, but are interested in building personal learning networks or simply seeking information.
Sullivan 2019 [65]	UK	39 Trainee doctors in an acute medical unit	Secondary	Survey	Advice	Degree; betweenness; density	Information and influence relating to different aspects of practice have different patterns of spread within teams of trainee doctors. Influencers in clinical teams have particular characteristics, and this knowledge could guide leaders and teachers.
Zappa 2011 [16]	Italy	711 Physicians	Secondary	Survey/Questionnaire	Knowledge sharing	ERGMs	Knowledge flows informally in mutual information-seeking relationships. Physicians tend to cluster in small groups of proximate and similar peers. The propensity to share knowledge is affected by individual-specific characteristics.
Aylward 2012 [47]	USA	286 Pediatric Psychologists	Primary and Secondary	Survey	Mentoring	Density; indegree; outdegree; closeness; betweenness; average geodesic distance	The field of pediatric psychology is interconnected with professionals learning from multiple mentors in multiple settings. The average “degrees of separation” between individuals in the network is 5.30.

Benammi 2019 [78]	Morocco	58 Members of an Acute Care Unit (ACU) in a university hospital	Secondary	Survey	Communication	Density; degree and betweenness centralization; degree and betweenness centrality	ACU network shows a moderate degree centralization, and lower betweenness centralization. The team is connected by well-positioned members to support inter-team communication, and is dominated by a number of gatekeepers, with low degree of communication among different function team members.
Bachand 2018 [66]	USA	8338 Women with breast cancer in 157 physician peer groups (made up of 16,171 physicians)	Secondary	Surveillance, epidemiology, and end results-Medicare data	Patient-sharing	Ingroup density; transitivity	Surgical delays vary substantially across physician peer groups, and are associated with provider density and patient racial composition. Women in physician peer groups with the highest provider density are less likely to receive delayed surgery.
Bae 2017 [33]	England, UK	54 Nurses in an acute care hospital unit	Secondary	Survey	Mutual support	Degree; closeness; betweenness; eigenvector density; shortest path; reciprocity; transitivity	Providers of mutual support claim to give their peers more help than these peers gave them credit for. Those who work overtime provide more mutual support.
Fong 2017 [43]	Taiwan	100 Multidisciplinary staff members in 3 Intensive Care Unit (ICU) in an academic teaching hospital	Secondary	Questionnaire	Communication	Cluster analysis (k-means)	Distinct patterns and categories of influencers (well-rounded, relational, and knowledge-based) are identified using a clustering approach. Knowledge of how influence is distributed across the care team could lead to a better planning of change initiatives.
Creswick 2010 [19]	Australia	45 Health professionals in a renal ward	Secondary	Questionnaire	Advice seeking	Geodesic distance; density; average strength of ties; reciprocity; degree; betweenness	On average, there is little interaction between each of the staff members in the medication advice-seeking network, with even less interaction between staff from different professional groups. Nurses are mainly located on one side of the network and doctors on the other. However, the pharmacist is quite central in the medication advice seeking network as are some senior nurses and a junior doctor.

Dauvrin 2015 [60]	Belgium	507 Healthcare professionals	Secondary and primary	Questionnaire	Problem-solving, advice-seeking, and socialization	Indegree	Cultural competence of the healthcare staff is associated with the cultural competence of the leaders. The leadership effect varied with the degree of cultural competence of the leaders.
Wong 2015 [36]	USA	98 Pediatric Intensive Care Unit staff	Secondary	Survey	Information seeking, social influence and social support	Degree; density	Amongst the 3 networks, there are no weakly connected groups. Few individuals report no links to a colleague. The number of links among colleagues is greatest for the information seeking network, followed by social influence, and social support. Five individuals, three of whom have formal leadership roles, are amongst the 10 most influential team members in all 3 networks.
Hurtado 2018 [67]	USA	38 Patient care workers	Community hospital	Survey	Advice seeking	Degree; reciprocity	There is a positive correlation between identifying more peers for safe patient handling advice and using equipment more frequently. Nurses with more reciprocal advice seeking nominations use safe patient handling equipment more frequently. However, nurses consulted more do not use equipment more frequently than nurses with fewer nominations.
van Beek 2013 [29]	Netherlands	391 Nursing staff from 37 long-term care dementia units	Community	Questionnaire	Communication	In-group density	In units with more networks between nursing staff and relatives of residents, staff treated residents with more respect and were more at ease with residents. Social networks were also positively related to staff's organizational identification which, in turn, related to their work motivation and their behavior towards residents.
Boyer 2010 [23]	France	104 Healthcare professionals in a hospital	Secondary	Questionnaire	Information sharing	Ingroup centrality; prestige; clique indicators	Centrality, prestige and clique indicators are highly correlated. Physicians have the highest scores for the three indicators. Older age is found to be associated with higher centrality and clique scores.
Anderson 2011 [56]	USA	Operating room staff (n=733 interdisciplinary	Secondary	Staffing data on surgical cases in the 29 operating rooms	Individual affiliation to surgical cases	Degree; closeness; betweenness; eigenvector; core/periphery	Both surgical services show a core/periphery network structure. Team coreness is associated with the length of the case. Procedure start time predicts the team coreness measure, with

		members) of 2 surgical specialties					cases starting later in the day less likely to be staffed with a high core team. Registered nurses constitute the majority of core interdisciplinary team members in both groups.
Brewer 2020 [75]	USA	268 Nursing staff in 24 Patient Care Unit (PCUs)	Secondary	Web-based questionnaire	Information sharing and advice seeking	Average distance; betweenness; clique count; clustering; density; diffusion; eigenvector; fragmentation; hierarchy; isolates; size; degree	In clinical workplaces with high day-to-day staff variation, several network characteristics remain stable over time. Hierarchy, fragmentation and cliques are unstable.
Lower 2010 [15]	Australia	13 Multi-disciplinary teams in hearing services	Community	Questionnaire and interviews	Information exchange; referrals; working relationships	Degree; average number of ties	Nurse audiometrists, WorkCover and agricultural retailers have the lead role in disseminating information on hearing health within the network. For client referrals the nurse audiometrists, private audiometry services, general practitioners, ear, nose and throat specialists and industry groups play the major roles.
Quinlan 2010 [17]	Canada	29 Nurse practitioners in primary-care teams	Community	Survey	Mutual understanding	Within-team density; flow-betweenness centralization	In two teams mutual understanding increases with time. In the other two teams, it decreases. As the overall mutual understanding within the team decreases, the facilitation of mutual understanding becomes more centralized among few team members; conversely, as mutual understanding increases, the facilitation becomes more equally distributed. The inverse relationship exists in all teams, except in team.
Edge 2019 [45]	UK	138 Foundation doctors in one NHS trust	Secondary	Observational study	Physical contact	Degree; density; density by groups; assortativity	Direct network links to vaccinated colleagues increase an individual’s likelihood of being vaccinated.

Espinoza 2018 [44]	Chile	53 Inter-professional teams (409 professionals) at a university hospital	Secondary	Questionnaire and interview	Advice and personal support	Density; isolates; centrality; Within-group cohesion	For the work advice network, when a team structures itself around one professional, this allows its members to approach and be approached easily and facilitates information exchange. Teams with the least satisfaction reveal a fragmented structure with members organized as subgroups. The organization of social support networks is even more fragmented, with half of them being isolated from the rest of the team.
Crockett 2018 [80]	Canada	22 Healthcare professionals in 18 general Emergency Departments	Secondary	Interviews	Information seeking	Content analysis	Health care professionals sought information both formally and informally, by using guidelines, talking to colleagues, and attending pediatric related training sessions. Network structure and processes were found to increase connections, support practice change, and promote standards of care.
Pomare 2018 [34]	Australia	23 and 27 Clinical and non-clinical staff members in 2 headspace centres	Youth mental health service	Survey	Collaboration, advice, problem solving	Degree; sub-group cohesion; density; centralization	Staff of headspace (clinical and non-clinical) show a tendency to collaborate with colleagues outside of their professional group, compared to within. Networks are well connected when staff collaborate in routine work and when faced with uncertainty in decision-making. There are fewer interactions during times of role uncertainty. The headspace centre that had been in operation for longer show greater indicators of cohesiveness.
Choudhury 2018 [81]	USA	3 Large-sized integrated delivery networks; 14 hospitals; 288 physicians; 353 prescriptions	Secondary	Medical prescriptions and affiliations datasets	Affiliation	Diffusion models	Physicians affiliated to same hospital and integrated delivery network contribute highly in the diffusion process. The weighted edge approach is better able to explain diffusion of influence in terms of prescribing patterns.
Palazzolo 2011 [68]	USA	3 Multidivisional healthcare teams (n=126 individuals) in 1 hospital	Secondary	Email archives	Communication	Betweenness; contribution index; group betweenness; core/periphery; density; structural holes; connectivity	SNA of email communications of three teams caring for patients with different complex long-term conditions reveal distinct patterns and structures. Team metrics varied over time. Teams' network characteristics may explain their functioning.

Hornbeck 2012 [46]	USA	Healthcare workers (HCW) and patients in 1 Medical intensive care unit	Secondary	Mote-based sensor network	Physical contact	Agent-based simulation	Electronic sensor derived data on HCW interactions with other HCW's and patients reveal that a small number of HCWs were responsible for a large number of interactions.
Shoham 2015 [41]	USA	69 Co-workers listed by 48 clinical team members in a burn intensive care unit	Secondary	Questionnaire	Communication	Degree; betweenness; density	The analysis revealed three distinct sets of team members caring for two sets of patients. The five clinical team members most central to the network included three physicians, a social worker, and a dietitian.
Zappa 2014 [83]	Italy	106 Oncologists	Virtual community	Emails	Cooperation	SAOMs	Emergent network effectively represented by a small number of local rules, i.e., actors' behaviors of counterpart's selection in their neighborhood.

Seventy-four studies were classified as Level-2. These are studies using SNA solely for descriptive or analytic purposes, without discussing about possible interventions aimed at changing or improving the structure or functioning of the networks. Twenty-three studies were from the USA, 14 from Europe (excluding UK), 14 from LMIC, seven from UK, nine from Australia, five from Canada and two from Japan. Forty-five studies used teams or mixed groups of healthcare professions as participants, 15 papers featured doctors only, 10 papers involved nurses, one study radiologists, one study psychologists, one also involved patients, and one had other types of healthcare professionals.

The majority of the studies (n=46) were set in secondary care settings, followed by community (n=9) and primary care settings (n=5). Eight studies were conducted in mixed secondary and community, and primary and secondary settings. Finally, three studies were set in virtual settings, one in a university hospital, one in a cross sector and one in a nursing home. Twenty-six papers relied on surveys to collect network data, 17 used questionnaires, 10 used logs or administrative data, seven were based on mixed methods, six on observation, four on interviews, two on online platforms or forums, and two on interaction data from sensors.

Ten different types of ties were examined, the commonest being information and knowledge exchange. Nine papers described more than one tie [15,34,36,44,60,64,72,75,92]. Twenty-nine different network measures were used to describe the networks at the individual, dyadic, group and whole network levels. Statistical analysis was performed as the only analytical method in 10 studies. Burt et al. [42] is a theoretical paper suggesting different types of questions for name generators. Forty papers (60%) were published between 2010 and 2015, and thirty-four (40%) between 2016 to 1st May 2022.

Level-3 studies

Table 3 below includes the level-3 studies, followed by a descriptive summary.

Table 3. The level-3 studies.

Ref	Country	Participants	Setting	Data collection	Type of tie	Network measure(s)	Key network findings	Recommendations	Network strategy
Xu 2021 [115]	China	5247 Healthcare Workers	Secondary	Survey	Discussion	Density; degree	A vaccination consulting network of 1817 members is reconstructed. The network shows low density. Twenty-two influential members are identified. Lack of discussion is associated with vaccine hesitancy. Department leads are particularly influential as promoters of vaccination.	Use influential individuals as role models to encourage vaccine uptake.	Individuals
Jippes 2010 [18]	Netherlands	81 Gynecologists and pediatricians and 63 residents in O&G and Pediatrics	Secondary	Questionnaire and interviews	Communication	Degree; closeness; betweenness	Social connections are more important than training for uptake of a new practice. A strong association is found between closeness centrality and adoptive behavior, and a moderate effect of degree centrality.	Incorporate individuals who have both strong and weak ties in 'teach-the-teacher' courses.	Individuals
Mascia 2018 [111]	Italy	97 Pediatricians in 2 Local Health Authorities (LHAs)	Community	Questionnaire	Advice	ERGMs	In both LHAs, physicians tend to reciprocate advice ties; there is considerable clustering in advice-seeking.	Create new opportunities for knowledge exchange, such as taskforces or training programs.	Induction
Llupià 2016 [97]	Spain	235 Healthcare workers in 1 hospital	Secondary	Interviews	Information exchange	ERGMs	Similarity in vaccination behavior does not play a significant role in the probability of being connected to another healthcare worker.	Use SNA to guide the design, implementation, evaluation of a health promotion campaign. For example, messages could be tailored by professional category or strategy could be implemented to foster communication among	Segmentation and induction

								different professional categories.	
Meltzer 2010 [102]	USA	56 Physicians attending on the general medical services in 1 hospital	Secondary	Questionnaire	Communication	Degree; Net degree of team; betweenness; density	Connections of team members outside the team are important for dissemination of information or influence. Connections of team members inside the team are important for within-team coordination, knowledge sharing and communication.	Use SNA to decide whom to select for a quality improvement team, and how to structure the team. When influence through direct social interaction is important, choose individuals who can reach the largest number of persons outside the team. The use of degree alone to select team members may produce many redundant ties.	Individuals
Polgreen 2010 [103]	USA	148 Multidisciplinary healthcare workers in 1 hospital	Secondary	Observational data and simulation	Physical contact	Number of contacts	Preferentially vaccinating healthcare workers in more connected job categories yield a lower attack rate and fewer infections in a simulation.	Identifying workers with many contacts might aid targeting vaccinations to optimize impact on flu spread.	Individuals
Mascia 2011 [24]	Italy	297 Hospital physicians in 6 hospitals	Secondary	Questionnaire	Advice	MRQAP	Physicians reporting similar attitudes toward evidence-based medicine (EBM) are more likely to exchange information and advice.	Foster heterophily when multidisciplinary cooperation is required. Identify groups exhibiting desired attitudes and behaviors. Adopt organizational arrangements, processes and informal meetings to foster collaboration.	Induction and segmentation

Sykes 2011 [22]	USA	151 Hospital physician in 1 hospital	Secondary	Survey	Advice	First degree centrality; second degree centrality	Both first-degree (direct) and second-degree (indirect) centrality negatively influence electronic medical records (EMR) system use. Physicians with more connections are less likely to be early users of EMR.	Be aware that resistance to EMR systems is greater among physicians with high centrality who should then be the target of resources to reduce such resistance.	Individuals
Pinelli 2015 [105]	USA	72 Multidisciplinary healthcare professionals in 1 hospital	Secondary	Interviews	Communication	Size; density; strength of tie; betweenness	Most communication is synchronous. Most communication events occur between the primary nurse and patient, and the care coordinator and primary nurse.	Improvements in discharges are possible by reorganizing systems to optimize communication. SNA could offer a cost-effective way to improve patient care provision.	Alteration
Mascia 2015 [107]	Italy	297 Hospital physicians in a Local Health Authority (LHA)	Secondary	Questionnaire	Information exchange	MRQAP	Institutional and professional homophily affect inter-physician networks. Professional homophily is more relevant than institutional affiliation for collaborative ties.	Foster collaboration across heterogeneous groups of physicians from different specializations.	Induction
Shoham 2016 [99]	USA	71 Multidisciplinary healthcare professionals in a hospital burn unit	Secondary	Survey	Discussion	Density; degree; ERGMs	Members of all roles are involved in a higher percentage of inter- than intra-professional ties. Physicians are most central to the network. Nurses are significantly more likely to connect with other nurses.	Consider purposefully developing the role of nurses within the team.	Segmentation
Gorley 2016 [106]	Canada	227 Participants in a BC Sepsis network	Secondary	Questionnaire and interviews	Knowledge sharing	Density; Centrality	Eleven participants stand out as hubs (high degree centrality). These individuals have many connections with people who trust them.	When launching a new network or strengthening an existing network for quality improvement,	Individuals and Induction

								several recommendations are offered (e.g., to seek and include distributed leaders in the network).	
Mascia 2013 [100]	Italy	297 Hospital physicians in 6 hospitals; 1 Local health unit	Secondary	Questionnaire	Advice	Coreness; network authority	The overall network shows a core-periphery structure. There is a negative association between physicians' attitudes toward evidence-based medicine (EBM) and the coreness they exhibited in the professional network. Network centrality indicators confirm a negative association between physicians' propensity to use EBM and their structural importance in the professional network.	Policy makers can foster collaboration across staff with different propensities to use EBM by relying on organizational arrangements, informal meetings, and use of medical leaders to persuade other professionals to collaborate more with EBM user.	Individuals and Induction
Creswick 2015 [101]	Australia	101 Hospital staff members in 1 teaching hospital	Secondary	Questionnaire	Advice	Density; reciprocation; indegree	Medication advice-seeking networks among staff on hospital wards are sparse, information sharing across professional groups is modest, and rates of reciprocation of advice is low. Senior physicians are weakly integrated into medication advice networks; pharmacists and junior physicians play central roles.	Policies to advance the advice-giving networks between senior and junior physicians may improve medication safety as one ward with stronger networks had lower prescribing error rate.	Segmentation
Marques-Sanchez 2018 [98]	Spain	196 Multidisciplinary healthcare professionals	Secondary and primary	Questionnaire	Internal and external advice	Outdegree (internal and external ties)	For physicians, external ties improve the performance at an individual and team level, yet external ties are not relevant for nurses' work performance.	Use SNA to facilitate healthcare professionals sharing information within and across organizations.	Alteration

Kothari 2014 [114]	USA	13 Public health practitioners	Community	Questionnaire and interviews	Interaction, support, and professional relationships	Cliques; degree; closeness; betweenness	Participants' report on their experience with SNA.	Use SNA as a reflective practice tool for professionals to assess their networks and strengthen collaborations. Assess team arrangements to identify the absence of key players or to recognize critical gaps in communication links that are necessary to work collaboratively.	Alteration and Individuals
Mundt 2019 [96]	USA	143 Healthcare professionals at 5 primary clinics	Primary	Survey	Communication	Core/periphery	Clinic employees in the core of the communication network have significantly greater job satisfaction than those who are on the periphery.	To increase clinicians' job satisfaction, foster face-to-face communication among all team members.	Alteration
Assegaai 2019 [110]	South Africa	Community health workers (CHW) (n= 37), ward-based outreach team (WBOT) leaders (N=3), primary healthcare facility (PHC) managers (N=5) and local area managers (N=2)	Community	Questionnaire	Interaction (supportive supervision)	Network graphs (indegree; density)	The supportive supervision system revolves around team leaders, who are nurse cadres and who ensure internal cohesion and support among WBOT members. The network patterns also show the extent of peer support between CHWs and WBOTs.	Relationships within teams work better than those between teams. Use SNA to identify relationships that could be strengthened.	Alteration
Tighe 2014 [112]	USA	A single day operating room (OR) schedule encompassing 32 anesthetizing sites	Secondary	Simulation and interviews	Interaction	Degree; betweenness; eigenvector	The OR is a scale-free network with small-world characteristics. There are differences in degree centrality between nurses and anesthesiologists and surgeons. Attendings have greater degree centrality than residents.	Use SNA to improve communication within ORs (e.g., by protecting a few highly-connected individuals; by placing senior staff into roles based on communication volumes).	Segmentation

Sykes 2015 [109]	Australia	171 Operating room (OR) staff members in 4 surgical teams in 1 hospital	Secondary	Electronic database	Interaction	Network graphs	Eighteen staff members are regularly shared across teams, including 12 nurses, five anesthetists, and one registrar. Weak but significant correlations is found between the number of staff, procedure start time, length of procedure, and patient acuity.	Use SNA to identify change champions who can support initiatives across multiple teams.	Individuals
Hossain 2012 [104]	USA	204 Outpatient departments (OPDs) and 458 emergency departments (Eds)	Secondary	National survey	Coordination	Degree; Density; centralization	The nurse is the actor with highest degree, followed by physician and lab technician. There is a significant relationship between degree and performance of coordination.	Use SNA to understand the possible causes of inefficient coordination performance and coordination quality resulting in access blocks.	Alteration
Li 2020 [108]	China	102 Hospital doctors	Secondary	Online forum	Communication and information exchange	Density; degree centralization; geodesic distance; centrality; reciprocity	Doctors are more closely connected, and information is easily spread. Doctors with higher professional titles show high levels of reciprocity. They are more likely to influence the behavior of other doctors.	Introduce clinical educational meetings to increase the frequency of doctor interaction at different levels.	Induction
Yousefi Nooraie 2017 [95]	Canada	14 Multidisciplinary public health staff	Public health centers	Interviews	Information exchange	Indegree	Information seeking networks evolve towards more centralized structures. Staff who are already central at baseline gain even more centrality.	Use SNA to support and inform the design, process and evaluation of the evidence informed decision-making training interventions.	Induction
Cannavacciuolo 2017 [113]	Romania	28 Multidisciplinary rehabilitation unit staff.	Rehab	Questionnaire	Advice and knowledge exchange	Centrality; frequency of interactions; in-group/out-group interactions	Knowledge is shared in a centralized network characterized by the presence of a few hubs and some marginal actors. The team members consult with a high number of external experts but these sources tend to	Redesign the team network to improve the efficiency and effectiveness of knowledge sharing. The re-design interventions concern three main features of knowledge	Alteration

							belong to personal networks and are not shared. Interpersonal knowledge exchange is mostly vertical than lateral.	network: “knowledge centralization,” “over-reliance on external experts”, and “unshared knowledge tools and sources.” Different strategies are discussed.	

Twenty-four studies were classified as Level-3. Nine were conducted in the USA, seven in Europe (excluding UK), two in Australia, two in LMIC, two in Canada and two in China. Twelve used teams or mixed groups of healthcare professionals as participants, nine studies used doctors, two had other health professionals and one used healthcare providers and patients. The majority of the studies (n=17) collected data in a secondary care setting, four in the community, one in primary care, one in primary and secondary care, and one in public health.

Ten studies used questionnaires to collect data, three relied on mixed methods, four used surveys, three interviews, two collected interaction data from sensors, one used direct observation, and one an online platform or forum. Seven different types of ties were analyzed across studies. Two studies analyzed more than one tie [113][108][114]. Twelve different network measures were used to describe or analyze networks at the individual, dyadic, group and whole network levels. Statistical analysis relying on ERGMs and MRQAP were used five times.

The four types of network interventions were mentioned as recommended strategies to be designed and implemented in order to improve the overall structure and functioning of the networks. Nine studies recommended to use 'individuals' [18,22,100,102,103,106,109,114,115], eight studies recommended ‘induction’ [24,95,97,100,106–108,111], seven studies discussed possible 'alteration’ strategies [96,98,104,105,110,113,114], and four recommended 'segmentation' [97,99,101,112]. Four studies recommended more than one strategy [97,100,106,114]. Thirteen papers were published between 2010 to 2015, and 11 between 2016 to 1st May 2022.

Discussion

We updated previous reviews by including papers published since 2010 that have used SNA to investigate networks among healthcare professionals. Our search strategy included a wide range of databases and placed no restrictions on professional groups, healthcare setting, country, or study design. We found 102 papers that used SNA to examine networks of healthcare professionals. We confirmed the findings of prior systematic reviews: The majority of published studies were descriptive, with only four papers discussing the outcomes of an SNA-based intervention. We defined network intervention as a set of actions aimed at modifying the main elements of a network system (i.e., nodes and relations) so as to generate behavior change and improve system performance. The main idea behind network intervention is that if networks affect outcomes of interest, change in network structure could lead to change in relevant outcomes.

A possible explanation for the limited number of studies on network interventions concerns the practical difficulties in designing and implementing network-based interventions in general, and in healthcare contexts more specifically. Valente et al. [5] discuss the main challenges associated with network interventions in the domains of public health and medicine. In what follows, we will briefly describe the main challenges that we believe arise when an intervention is designed and implemented within an organizational context, such as a hospital or other healthcare organizations. Healthcare organizations present additional challenges over and above those identified by Valente et al. [5] for the public health domain. We organize our discussion by using the four-stage model of program implementation suggested by Valente et al. [5].

<u>Exploration</u>. The first stage involves the assessment of a community in terms of needs, vision and opportunity for change [5]. In practice, this implies identifying: (i) a well-defined network (i.e., community boundaries); (ii) the relations among community members (i.e., social

capital); (iii) the specific interests of various stakeholders, and (iv) the behavior under investigation. A number of specific challenges may arise at this stage when social network research is conducted within organizations [116]. First, network identification. This may be facilitated by the natural boundaries that organizations provide for the network of interest. Problems typically arise in collecting the non-anonymous data needed for network research. The management of the organization (which is often also the commissioner of the research) may provide partial commitment or discontinued support to the research, or even restricted access to data. Access to network and other types of data may also be problematic due to the specific nature of the population under investigation. Intervention programs within healthcare organizations are likely to involve multiple professional groups (e.g., hospital administrators, medical doctors, nurses, etc.) whose interdependencies may be difficult to manage or predict thoroughly *ex ante*. The actual use of output data from hospital administrators, participants' protection of ethical rights, as well as the existence of ethical codes for professionals are all factors that may make data collection within healthcare organizations particularly challenging [117]. A solution to this problem may be a clear identification and communication of the goals and objectives of the research. The four studies that we identified as reporting the results of a network intervention (level-1), or those recommending a follow-up intervention in their conclusion section (level-2), mainly focused on improving specific structural features of the networks. Of the four level-1 studies, only two measured the impact of network intervention on health-related outcomes [27][25]. The reason for this may lie in the difficulty of envisioning clear-cut causal links between behaviors at one level (e.g., health professionals) and outcomes at another level (e.g., patients). More direct evidence of measurable outcomes of network interventions at the patient or organizational level is needed. Finally, ethical challenges should also be considered at this stage. Cronin et al. [118] and Borgatti and Molina [119] offer explicit guidance on how to deal with specific ethical issues such as protecting anonymity, presenting output data in aggregated form, and offering participants multiple opportunities for opting-out.

Adoption. The second stage involves the creation and adoption of an intervention program to address a behavioral problem [5]. The use of network analysis is particularly helpful at this stage, as it provides valuable information that can be used to tailor an intervention to the specific needs of the population under investigation. High response rates and lack of missing data are crucial as they allow to design an intervention based on more complete information. The identification of opinion leaders within a network who may act as change agents has been used in a large number of studies. Also, network analysis may be useful at this stage to identify other roles or positions, cohesive subgroups, or important cleavages within a network structure. Within an organizational setting, the existence of a formal reporting structure is particularly relevant in that it provides additional information on power structures and formal roles that can also be leveraged in a network-based intervention.

Implementation. The third stage involves implementing the program with adherence and competence [5]. Within healthcare organizations, pressures to improve outcomes (e.g., clinical, operational, financial and managerial) are frequently generated by policy changes that produce top-down initiatives proposed by senior management and implemented through the involvement of various organizational change agents such as medical doctors, hospital administrators and, occasionally, technical and support staff. Research has recognized that the success of change initiatives hinges on the ability of change agents to overcome potential resistance from other organizational members, and encourage them to adopt or develop new practices [120]. In professional organizations, such as healthcare organizations, the coexistence of many professional groups with strong identity and role boundaries may represent the biggest obstacle to organizational change. Furthermore, not all change initiatives are equivalent, and recent research has pointed to the need of establishing the extent to which a change initiative diverges from the institutional status quo in order to better identify factors enabling adoption [120]. Other than resistance to, and extent of, change, challenges that may arise at this stage include availability of resources needed to implement a change program, lack of evidence of successful research designs to use in non-experimental, organizational settings, and lack of clarity about outcome variables to be monitored during the implementation stage.

Sustainment. The fourth, and last stage involves checking that the program continues to be implemented as intended over time, and is continuing to exert the anticipated effects [5]. The main challenge at this stage concerns the slow-moving nature of network and organizational variables, compounded by the often-far too high turnover rates within organizational units. This could make particularly difficult predicting with a reasonable level of certainty how long a social structure would take to affect a behavior, or an outcome of interest. As this usually takes time, problems may arise that are related to changes in the composition of a network structure, which should ideally remain unchanged for the duration of an intervention program. In non-experimental, naturalistic settings this is unlikely to occur. Research has also shown that changes in the composition of a network structure led to changes in the attitudes and behaviors of those who remain in the organization [121].

We have not offered specific solutions to the various issues highlighted above. Rather, our aim was to shed light on the main challenges of implementing a change initiative within an organizational setting. A possible solution to some of the challenges associated with implementing an intervention and measuring its effects over time is the adoption of a simulation-based analytic approach. This approach involves data collected on an existing network to simulate a number of alternative scenarios resulting from altering specific characteristics of the nodes and ties within a network. An example of application of a simulation-based approach to a longitudinal network dataset can be found in Schaefer et al. [122]. The authors use the results of Stochastic Actor-Oriented Models to simulate the coevolution of friendship ties and smoking behavior under potential intervention scenarios. Currently available statistical models for network data have the advantage of being particularly well-suited for simulation analyses. This is an approach that we believe may provide realistic and interpretable evidence of the possible outcomes of a change initiative, and may justify the long-term resource commitment that network-based interventions usually require.

While a number of studies are available that describe network structure, it is important to consider that research informing on how to make positive changes in networks is likely to be closer to having practical impact. There is an urgent need for more research into which healthcare network interventions work in different contexts and how they can be best designed and employed. Similarly pressing is a need for further work to identify experimental design options that are more effective at identifying and maximizing control over relevant variables and outcomes, and that are more efficient in terms of time and resource needed. We may conclude that this is an important opportunity for the field to coalesce on terminology, measures, and applications, after establishing priority areas for researchers in how to do so to advance work on the application of SNA to the design, dissemination, implementation and sustainability of behavior change interventions.

Limitations: We used a comprehensive broad approach to searching but may have missed some research results such as unpublished conference proceedings, papers not available in English language, negative findings or studies that did not complete and were not submitted, and grey literature.

Conclusion

Studies of network intervention remain scant and devoid of implications for the impact of intervention initiatives on patient care. There is a need for evidence on which kinds of network interventions work, in which contexts, and under what conditions - or for whom. It is possible to measure the effect of an intervention on network effectiveness, for example, by measuring the number of new links or increased volume of communication. However implicitly, this approach assumes a causal link between inter-professional communication and patient benefits. The complexity of healthcare, and the ubiquitous nature of barriers to best practice, implies that this is often a conjecture too far, and a more direct evidence of patient benefit should be preferred. The most important test of the effectiveness of network intervention would be assessing its impact on patient level outcomes, or, when this is difficult to determine, on the delivery of processes of care that are supported by good evidence.

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Supporting information

S1 Table. Database results.

S2 Table. Types of network ties.

S3 Table. Network Measures.

S1 File. Search Strategy.

S2 File. PRISMA-ScR checklist.