Using Technology to Measure Older Adults' Social Networks for Health and Well-Being: A Scoping Review

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Funding

Partial support for this manuscript was provided by Duke University School of Nursing Center for Nursing Research Population Health Pilot Award, “Network-Level Measures of Well-being among People Living with Dementia” (Corazzini and McConnell MPIs), to SW, ESM, KWF, MT, BK, and KC. Additionally, this manuscript was partially supported by Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education(grant number: 2020R1A6A1A03041989) to BK.

Conflicts of interest

The authors declare no conflicts of interest.

Abstract

Background and Objectives: Social networks impact the health and well-being of older adults. Advancements in technology (e.g., digital devices and mHealth) enrich our ability to collect social networks and health data. The purpose of this scoping review was to identify and map the use of technology in measuring older adults' social networks for health and social care.

Research Design and Methods: Joanna Briggs Institute methodology was followed. PubMed (MEDLINE), Sociological Abstracts, SocINDEX, CINAHL, and Web of Science were searched for relevant articles. Conference abstracts and proceedings were searched via Conference Papers Index, the American Sociological Society, and The Gerontological Society of America. Studies published in English from January 2004 to March 2020 that aimed to improve health or social care for older adults and used technology to measure social networks were included. Data were extracted by two independent reviewers using an a priori extraction tool.

Results: The majority of the 18 reviewed studies were pilot or simulation research conducted in Europe that focused on older adults living in the community. The various types of technologies used can be categorized as environment-based, person-based, and data-based.

Discussion and Implications: Technology facilitates objective and longitudinal data collection on the social interactions and activities of older adults. The use of technology to measure older adults' social networks, however, is primarily in an exploratory phase. Multidisciplinary collaborations are needed to overcome operational, analytical, and implementation challenges. Future studies should leverage technologies for addressing social isolation and care for older adults, especially during the COVID-19 pandemic.

Keywords: Technology, Measurement, Aging in Place, Social Isolation, Social Networks

Social networks play a critical role in ensuring older adults' health and well-being; they can contribute to chronic illness management, prevent decline in physical and cognitive function, and enhance health care utilization (Cornwell & Laumann, 2015; Litwin & Stoeckel, 2014). Social networks influence health via social support, social influence, social engagement, interpersonal interactions, and access to social resources (Smith & Christakis, 2008; Song, 2013). The surge and spread of COVID-19 has increased awareness of the social determinants of health and has enhanced research interest in the influence of social networks on health care for older adults, particularly regarding infectious disease control in nursing homes, social isolation due to quarantine, social support, and access to social resources (Abrams & Szefler, 2020; Holmes et al., 2020). Because positive relationships that are established and maintained through social networks can be a critical source of support for older adults experiencing a decline in functional status due to chronic conditions, there is increased interest in leveraging older adults' social networks in order to develop novel interventions to improve their health-related and psychosocial outcomes. The first step in developing social network interventions is to identify reliable and feasible measures to assess the social networks of older adults.

Traditional methods of collecting data and assessing social networks (e.g., standardized measures administered through questionnaire or interviews, or direct observations) can be time-consuming, expensive, and cognitively burdensome; in addition, they risk compromised validity and reliability due to social desirability, response quality, and interviewer effects (Morris, 2004; Perry et al., 2018; Valente, 2010). Rapidly evolving technologies such as electronic and digital devices, social media, and health care technologies (e.g., mobile health applications (mHealth), electronic health records) may address the limitations of traditional methods. Studies have found that older adults have high use of technologies such as cell phones, and that they adopt newer technologies similarly to other age groups (Banbury et al., 2017; Nouri et al., 2020). Thus, studies of how new technologies can be used to measure social networks and their capture of social interaction phenomena in real-world settings could contribute to a subsequent understanding of the impact of social networks on older adults' health and well-being.

Evidence of the impact of social networks on health outcomes for older adults combined with advancements in technology to overcome methodological challenges associated with measuring social networks suggests that a review of the literature is needed. A better understanding of how technology has been used to measure the social networks of older adults may improve successful leveraging of technology and social networks to enhance health and well-being for this population; therefore, the purpose of this scoping review was to identify and map technologies used to measure social networks related to older adults' health and social care. Specifically, the research questions were as follows:

1. In what settings of health or social care have these measures been developed or tested?
2. How have these measures been used in discovery science, implementation science, and clinical care?
3. What are the existing approaches that use technology for measuring older adults' social networks?

Methods

Our scoping review followed the Joanna Briggs Institute (JBI) methodology to examine rigorously the nature and extent of emergent and heterogeneous research (*Joanna Briggs Institute Reviewer's Manual*, 2018; Peters et al., 2015). A scoping review protocol that outlined the approach was developed and published (Wei et al., 2020). Since our goal was not to evaluate the quality of evidence, we did not include quality appraisal tools in our methods. A summary and further description of the methods are outlined below.

Data Sources and Search Strategy

The search strategy adhered to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement (see Supplementary Material) (Moher et al., 2009). We employed a three-phase strategy as described in the protocol to ensure a comprehensive search of peer-reviewed published literature and grey (unpublished) literature (Wei et al., 2020). We used the core elements of inclusion criteria in the JBI Scoping Review methodology to design three categories of search syntax: older adults (participants), measurement of social networks using technology (concept), and health and social care (context). The search was translated and tailored for each database using appropriate subject headings and consistent keywords across information sources. Given our focus on technology, we included search terms for data mining techniques in addition to more conventional measures. The information sources we searched include PubMed (MEDLINE), Sociological Abstracts, SocINDEX, CINAHL, Web of Science, and Conference Papers Index. In addition to searching grey literature through Conference Papers Index, we hand-searched conference proceedings from the American Sociological Society and The Gerontological Society of America. The full search strategy for each database is available in Supplementary Material.

Selection Criteria

We included studies that (a) incorporated technology to assist or modify measurement of social networks, (b) focused on older adults as the targeted population, (c) related to health or social care, (d) had sufficient information and results about the measurement of social networks using technology, and (e) were published in English between January 2004 and March 2020. We excluded books, editorials, letters, dissertations, reviews, commentaries, and studies without reported results.

Screening

Results from databases were exported into EndNote (Clarivate Analytics, PA, USA) and then imported into a systematic review software, Covidence (Veritas Health Innovation, Melbourne, Australia) to facilitate the screening process. All aspects of screening, including abstract and full-text reviews, were performed by two independent reviewers (SW, BK, YL, MT, KWF, TX). Any disagreements between reviewers were resolved by a third reviewer.

Data Extraction and Evidence Synthesis

The structured abstracting matrix reported in the protocol was pilot tested. Five researchers (SW, YL, MT, KWF, TX) coded two articles to test the usability of the original extraction tool. We modified the matrix table to better illustrate the study characteristics and measurement of social networks. After pilot testing, consensus was reached among the researchers, and an extraction manual was created to ensure coding consistency. Included studies were imported into QSR International's NVivo 11 software to facilitate the extraction as well as consensus on coding between two reviewers. The paired reviewers for extraction were strategically assigned to ensure that each pair included one native English speaker**,** one nursing scientist, and one person with research experience related to social networks.

Results

Search Outcomes

The search yielded 3555 articles. After duplicates were removed (n=741), 3412 articles remained for review at the abstract level. Of these, 230 articles were selected for full-text review to assess their relevance to our inclusion criteria, and 18 articles were included for the review. During screening, the bibliographies of the 18 articles and relevant review articles (n= 598) were checked for additional relevant articles, and the snowballing did not add any articles. The screening process is shown in the PRISMA flow diagram (See Figure 1).

Category of Technology

We categorized the technologies in the included articles into three groups to allow us to compare similar articles and enable discussion of their overall advantages and disadvantages (Table 1). *Environment-based* technology is hardware designed for and installed in living spaces such as in private homes (Bilbao et al., 2016; Campos et al., 2014; Chen et al., 2007; Cook et al., 2010; Peter et al., 2013; Rebola et al., 2013; Yu et al., 2015). This technology includes passive infrared and radio frequency sensors, internet of things, and video and audio recordings. The data collected by this technology is usually restricted to the space in which it is installed (e.g., occupancy, movement, and types of activities happening in the space). Although environment-based technology can detect multiple people, it may have difficulty distinguishing among people in the space.

Person-based technology is hardware that is wearable. This technology includes cameras and global positioning system (GPS) sensors in smartphones, accelerometers, and heart rate detectors installed in smartwatches and wearable sensors (Burns et al., 2014; Campos et al., 2014; Duval et al., 2018; Masumoto et al., 2017; Muller et al., 2013; Vanhems et al., 2013). Proven advantages of person-based technology are that they are well-established and easy to use, available at low cost, and capable of distinguishing individuals. Some researchers have used these sensors to infer face-to-face interactions (although perhaps not the type of activity). Person-based technology may be susceptible to data loss depending on its battery life and can detect only people who wear the sensors.

Data-based technology includes existing platforms (such as Facebook and electronic medical records) or custom-designed services or platforms (such as websites and mobile apps) that actively collect data or contain data which can be mined (Kennedy et al., 2016; Mo et al., 2018; Pfeil et al., 2011; Pfeil & Zaphiris, 2009; Quintana et al., 2019; Uddin et al., 2016). Extracting data from existing services or platforms may allow directional communication patterns to be detected easily; however, the data must be available and accessible. Developers can custom-design platforms around the purpose of their study, but development may be costly.

Study Characteristics

Most of the studies were pilot, simulation, or observational research (n =14) (Bilbao et al., 2016; Burns et al., 2014; Campos et al., 2014; Chen et al., 2007; Cook et al., 2010; Duval et al., 2018; Masumoto et al., 2017; Mo et al., 2018; Muller et al., 2013; Pfeil & Zaphiris, 2009; Quintana et al., 2019; Rebola et al., 2013; Uddin et al., 2016; Vanhems et al., 2013) and most were conducted in European countries (n = 9) (Bilbao et al., 2016; Burns et al., 2014; Duval et al., 2018; Kennedy et al., 2016; Muller et al., 2013; Peter et al., 2013; Pfeil et al., 2011; Pfeil & Zaphiris, 2009; Vanhems et al., 2013). All the studies focused on an older adult population, but only 10 studies selected older adults as their study participants (Campos et al., 2014; Kennedy et al., 2016; Masumoto et al., 2017; Mo et al., 2018; Peter et al., 2013; Pfeil et al., 2011; Pfeil & Zaphiris, 2009; Rebola et al., 2013; Uddin et al., 2016; Yu et al., 2015). Four out of 18 studies had sample sizes less than ten people (Bilbao et al., 2016; Burns et al., 2014; Cook et al., 2010; Yu et al., 2015)), and only five had sample sizes larger than 100 (Campos et al., 2014; Duval et al., 2018; Mo et al., 2018; Quintana et al., 2019; Uddin et al., 2016). Of the various settings where the studies were conducted, the most common settings were the community (n = 8) (Bilbao et al., 2016; Burns et al., 2014; Campos et al., 2014; Kennedy et al., 2016; Masumoto et al., 2017; Peter et al., 2013; Quintana et al., 2019; Rebola et al., 2013) and formal health care facilities (i.e., residential long-term care and hospital settings; n = 5) (Chen et al., 2007; Duval et al., 2018; Muller et al., 2013; Uddin et al., 2016; Vanhems et al., 2013).

Reviewed studies had four main purposes: (1) to promote *aging in place* or *active aging* (Boudiny, 2013; Wiles et al., 2012) by maintaining autonomy, improving independence, and decreasing social isolation of older adults in the community (Bilbao et al., 2016; Burns et al., 2014; Campos et al., 2014; Cook et al., 2010; Masumoto et al., 2017; Peter et al., 2013); (2) to improve older adults' or care providers' care management (Kennedy et al., 2016; Muller et al., 2013; Uddin et al., 2016; Yu et al., 2015); (3) to understand older adults' social interactions online or in retirement communities (Mo et al., 2018; Pfeil et al., 2011; Pfeil & Zaphiris, 2009; Rebola et al., 2013); and (4) to trace interpersonal interactions for nosocomial infection control (Duval et al., 2018; Vanhems et al., 2013). Six studies reported their theoretical foundations: Four studies were guided by social network theories such as centrality theory and social roles theory (Mo et al., 2018; Pfeil et al., 2011; Pfeil & Zaphiris, 2009; Uddin et al., 2016), one study was guided by a mixture of sociological and health theories (i.e., the influence theory, normalization process theory, and collaborative deliberation theory) (Kennedy et al., 2016), and one study was based on theories of infectious disease transmission (Vanhems et al., 2013). Although they specified no theories, most studies (n = 10) supported their research with empirical evidence regarding social support or interactions and their importance to the health and wellbeing of older adults (Bilbao et al., 2016; Burns et al., 2014; Campos et al., 2014; Chen et al., 2007; Cook et al., 2010; Masumoto et al., 2017; Peter et al., 2013; Quintana et al., 2019; Rebola et al., 2013; Yu et al., 2015). All but one of the studies were classified as discovery science; one was classified as implementation science (Kennedy et al., 2016). Most authors of reviewed articles were from computer science and engineering fields. Only six studies had coauthors from health science (Duval et al., 2018; Kennedy et al., 2016; Masumoto et al., 2017; Quintana et al., 2019; Uddin et al., 2016; Vanhems et al., 2013). The characteristics of the 18 studies are summarized in Table 2.

Using Technology to Measure Older Adults' Social Networks

Technologies that measure social networks capture and process various types of data and a range of social network elements. Supplementary Table S1 explains (a) how data were collected and processed in each study using specific technologies, (b) which social network elements were analyzed using either an eco-centric or socio-centric approach, (c) the strengths and limitations of the specific technologies used, and (d) the extent to which the technologies were accepted by participants. Sensors were the technology most often used for capturing network members, activities, or social interactions. For example, wearable Radio Frequency Identification (RFID) sensors identify participants by tracking sensor identifications and interactions from face-to-face proximity (Duval et al., 2018; Muller et al., 2013; Vanhems et al., 2013). Sensors embedded in a smart environment captured activities or social interactions, such as turning on lights and opening doors (Bilbao et al., 2016; Campos et al., 2014; Chen et al., 2007; Cook et al., 2010; Peter et al., 2013; Yu et al., 2015). In addition to using technologies to collect data, three studies specified how they used computer algorithms to process the collected data to better detect or analyze social interactions and emotions automatically (Campos et al., 2014; Chen et al., 2007; Cook et al., 2010). Most studies (n = 12) did not report the sampling rate or provide sufficient details for determining the sampling rate (Bilbao et al., 2016; Campos et al., 2014; Cook et al., 2010; Duval et al., 2018; Masumoto et al., 2017; Mo et al., 2018; Peter et al., 2013; Pfeil et al., 2011; Pfeil & Zaphiris, 2009; Quintana et al., 2019; Rebola et al., 2013; Uddin et al., 2016). Studies in which it was reported provided widely varying sampling rates, including (a) 30 frames per second for a study that used camera recording (Chen et al., 2007); (b) every 10 to 30 seconds for the three studies that used sensors (Burns et al., 2014; Muller et al., 2013; Vanhems et al., 2013); (c) twice daily which aligned with medication schedule (Yu et al., 2015); and (d) at 2-weeks, 6-months, and 1-year for subjective network mapping along with qualitative interviews (Kennedy et al., 2016). Study period of data collection from individuals ranged from 2.5 hours (Burns et al., 2014) to 52 months (Quintana et al., 2019).

Social network analysis used in these studies, which were categorized according to their use of an egocentric or sociocentric approach, allowed researchers to focus on interdependent relationships and social structures, as summarized in Supplementary Table S1. All studies used technology to record relational or behavioral data, such as face-to-face proximity and communication or interaction with others. These data can be processed to indicate relationships or connections (ties) between users of technology (nodes) for social network analysis. All studies reported network size by detecting the number of nodes or ties in networks, while a few studies also examined characteristics of network structures, such as density and centrality (Mo et al., 2018; Pfeil et al., 2011; Pfeil & Zaphiris, 2009; Yu et al., 2015). Ten studies (Chen et al., 2007; Duval et al., 2018; Masumoto et al., 2017; Mo et al., 2018; Muller et al., 2013; Pfeil et al., 2011; Pfeil & Zaphiris, 2009; Rebola et al., 2013; Uddin et al., 2016; Vanhems et al., 2013) measured social networks using a socio-centric approach when a single "complete" or "whole" network showing connections among all participants was evaluated (Perry et al., 2018). The remaining studies (Bilbao et al., 2016; Burns et al., 2014; Campos et al., 2014; Cook et al., 2010; Kennedy et al., 2016; Mo et al., 2018; Peter et al., 2013; Quintana et al., 2019) used an egocentric approach when separate networks were reported by participants as the egos (Perry et al., 2018). The majority of studies were at the early stage of feasibility testing and did not report reliability or validity of their measures. Only one study validated technology-based assessments of social networks against a validated psychological mechanism (the Lubben Social Network Scale) and showed minimal agreement (Kappa statistic = 0.1048) (Campos et al., 2014). Six studies reported efforts to improve reliability by checking inter-rater reliability by validating with experts' identification of social interactions (Chen et al., 2007; Pfeil et al., 2011; Pfeil & Zaphiris, 2009), testing test-retest reliability (Cook et al., 2010), or testing parallel-forms reliability by comparing data across different sensors (Peter et al., 2013; Rebola et al., 2013).

Most of the technologies were effective and easily collected social activity and interaction data to map social networks. Technology enabled the collection of large volumes of data (Pfeil et al., 2011; Pfeil & Zaphiris, 2009) as well as data with a high spatial and temporal resolution, long duration, and temporal consistency between video and audio (Chen et al., 2007; Duval et al., 2018). Using data collected from technologies to visualize social networks helped people to understand their social relationships (Kennedy et al., 2016; Rebola et al., 2013). Lastly, technology lowered energy consumption and reduced the maintenance effort during data collection because external observers were not needed (Muller et al., 2013; Vanhems et al., 2013).

A few common limitations of using technology to measure social networks among older adults were identified. For example, one sensor system did not recognize different individuals when they were in a shared location (Bilbao et al., 2016). Data security and privacy issues (such as video surveillance) were significant concerns (Muller et al., 2013; Rebola et al., 2013; Yu et al., 2015). Additionally, based on the studies that reported acceptance of the technology (n = 8), acceptance may be hindered by misconceptions about the technology or by lack of knowledge, familiarity, support, or ease-of-use (Burns et al., 2014; Kennedy et al., 2016; Mo et al., 2018; Muller et al., 2013; Peter et al., 2013; Quintana et al., 2019; Vanhems et al., 2013; Yu et al., 2015). Five studies demonstrated good acceptance either by reporting participants' response (Burns et al., 2014; Muller et al., 2013; Yu et al., 2015) or by showing high participation rate or usage (Mo et al., 2018; Vanhems et al., 2013). Two studies showed that users found the technologies useful although they had low usage when not guided by trained facilitators (Kennedy et al., 2016) or supported by family (Quintana et al., 2019). Negative feedback on bulkiness and difficulty of use were also reported (Muller et al., 2013). One study's report of acceptance from young volunteers who self-rated as experts in technological expertise may not reflect acceptance by their target population: older adults with dementia (Burns et al., 2014).

Discussion

Classifying technologies into environment-based, person-based, and data-based approaches provides researchers and clinicians with a framework to systematically evaluate the advantages and disadvantages of various options and can also facilitate decision-making regarding appropriate technologies based on settings, targeted aspects of social networks, and purposes. Data retrieved as digital traces left during technology uses or actively collected from technology can be mined to illuminate various aspects of social networks. The most obvious advantage of using technology is its ability to collect data longitudinally on nodes (people) and ties (connections or interactions) in large quantities, in real-time, and at a low cost. Technology can detect network members and provide objective measures of social interactions by analysis of data from sensor networks to measure behaviors related to social engagement, such as interpersonal proximity, types of physical activities, and frequency and duration of communication. Sensor-collected quantitative behavioral data can also be used to infer the quality of ties among network members; for example, detecting hugs or regular long phone conversations between two individuals can infer strong ties between two nodes. Some custom-designed web-based tools in reviewed studies also digitally collected subjective data on types or quality of ties such as emotionality of conversations or identification of a family member who provides care support (Pfeil et al., 2011; Pfeil & Zaphiris, 2009; Quintana et al., 2019). Data collected from technologies are convenient for implying quantities of social ties (e.g., time spent, frequency); however, with careful operationalization and validation, these data can be used to imply the quality of ties (e.g., closeness, meaningfulness).

Social networks have boundaries that delimit one's social system. Depending on the technological approach, the network boundary may be limited by geography (in the case of sensors installed in the environment) or social scope (in the case of archived data). The environment-based approach is fixed by the size of the setting in which the technology is implemented. A person-based approach is fixed by the mobility of the person and their use of a given technology. Data-based approaches are limited by the network of data that is collected and accessible for use. Researchers need to choose and implement specific technologies by considering feasibility based on the advantages and disadvantages of technologies to achieve study aims in their study context. Mixing different technologies and approaches may provide richer and more accurate data and broader network boundaries, much work remains to be done. Additionally, designing simple, small or lightweight, easy-to-use, and low-maintenance systems and providing technological support for older adults may improve their acceptance of a technological system.

The goals of improving aging in place, social connection, care management, and infection control are particularly relevant in the era of COVID-19. The pandemic has revealed the importance of measuring social networks to understand whether infection control practices such as physical distancing are being maintained and how best to maintain social connections and well-being while staying in place (Block et al., 2020; Van Orden et al., 2020). We completed our database search at the end of March 2020, during the early stage of the COVID-19 pandemic. Although none of the reviewed studies addressed COVID-19, technology is likely to become an inseparable part of work, socializing, and health care delivery in the future due to the pandemic. For example, cell phone data are being used to trace social contacts and control infection spread (Urbaczewski & Lee, 2020), and telemedicine allows patients to connect with providers while staying in place (Hollander & Carr, 2020). Technologies used to trace and mitigate COVID-19 have the potential to be leveraged to enhance understanding of social behaviors, improve social connectedness, and provide support and care to aging populations. We provide two hypothetical situations in which a mixture of technological approaches could measure aspects of older adults' social networks and provide directions for future research and implementation efforts.

Scenario 1: Nursing Home (Environment-Based Mixed with Person-Based Approach)

Residents of skilled nursing homes are vulnerable to infection and risks associated with social isolation. Given the challenges of monitoring people for changes in condition and habits while maintaining appropriate physical distance (infection control protocols), sensor technology could help staff understand how resident interaction patterns have changed and whether sufficient physical distancing is being maintained. Environment-based technology such as sensors or video cameras placed in resident rooms or in congregate areas would allow facility staff to determine how often and for how long a resident comes into contact with other people.

Coupling those fixed sensors with person-based proximity sensors such as RFID tags on name badges would enhance the information gleaned to allow understanding of the duration of direct interaction with specific individuals. These data could be combined with resident or staff ratings of emotional expression or well-being to determine the critical amount of social interaction required to maintain emotional well-being.

Scenario 2: Care Management in the Community (Data-Based Approach)

Mr. P(atient) has heart failure and lives alone. He has experienced increased shortness of breath and edema lately but fears he could catch COVID-19 if he goes to a health care facility. His heart rhythms are monitored remotely via data sent from his implanted pacemaker. The remote monitoring nurse has noticed that Mr. P has had consistently abnormal heart rhythms over the past three days, so she accesses his providers' care coordination network, a social network diagram mapped by the electronic health system based on providers' collaboration behaviors during previous care delivery for Mr. P. The nurse quickly identifies and alerts a nurse practitioner (NP) in Mr. P’s primary care provider network as well as a cardiologist (C1) from Mr. P's cardiology team.

Upon receiving the alert, the two providers discuss modifications to Mr. P’s care plan to address volume overload, a possible trigger of the detected tachyarrhythmia. The NP initiates a video conference with Mr. P to discuss his medical needs. The social networks mapped by Mr. P’s phone based on his call as well as text logs and GPS data alert the NP to changes in his social behaviors. He has not visited any public spaces with the exception of regular trips to a McDonald's drive-through, and his communications with family and friends have decreased since the beginning of the lockdown. The NP and Mr. P discuss these social and behavioral changes in addition to his medical concerns and identify strategies to improve his diet, reestablish connections with family and friends, identify safe recreational activities, and access needed health services while maintaining physical distance.

Accelerated innovations and developments in technological systems to measure social networks may provide solutions to the challenge of balancing infection control with social well-being during the COVID-19 era; however, current research is at an early stage. Currently available studies use small sample sizes, have limited generalizability, and would benefit from interdisciplinary collaboration to increase rigor and strengthen the quality of evidence. Majority of the studies included in this scoping review were pilots, simulations, or observational studies (Bilbao et al., 2016; Burns et al., 2014; Campos et al., 2014; Chen et al., 2007; Cook et al., 2010; Duval et al., 2018; Masumoto et al., 2017; Mo et al., 2018; Muller et al., 2013; Pfeil & Zaphiris, 2009; Quintana et al., 2019; Rebola et al., 2013; Uddin et al., 2016; Vanhems et al., 2013); these lacked rigorous study designs and control groups. Most studies were at the early stage of establishing feasibility and improving reliability, so they lacked examination of validity. Few studies reported sampling rate, and sampling rate varied depending on the type and use of technology. The only study that evaluated criterion validity showed minimal agreement. Future studies could improve reporting of validity and sampling rate and should consider whether the construct inferred from longitudinal recording of behaviors measured by technologies is the same construct that is measured by participants' subjective rating on traditional questionnaires when trying to establish criterion validity.

There were few coauthors from health science and only one study from implementation science (Kennedy et al., 2016), indicating a need for multidisciplinary work in this area. Multidisciplinary collaborations that avoid discipline-specific jargon make technologies more accessible and understandable across fields, thus reducing length of time from development and feasibility testing to implementation and clinical care. Additionally, ensuring explication of underlying social network and health theories across studies in this interdisciplinary field may improve the understanding of mechanisms behind social determinants of health. Only one-third of reviewed studies described foundational social network or health theories informing their study designs. These studies tended to study phenomena beyond node- or tie-level social network characteristics by assessing the group- or network-level characteristics, such as network position and centralization. Studies that did not report a theoretical framework related their work to the broader recognition that social relationships or supports are important for health and wellbeing. Better integration and explication of social network theories in future studies may improve the interpretation of findings beyond the basic level of nodes and ties, as well as facilitate bridging disciplinary perspectives to advance our understanding of the social structure and processes behind the effects of social relationships on the health and wellbeing of older adults.

Limitations

We reviewed articles in academic journals only and did not search for technological products developed and investigated in industry. Studies published in non-English languages were omitted.

Conclusions

Technologies used to measure older adults' social networks are complex and are currently in an exploratory phase. Although operational, analytical, and ethical challenges exist (Muller et al., 2013; Rebola et al., 2013; Vayena et al., 2015; Yu et al., 2015), technology makes it easier to collect data objectively and longitudinally by tracking social interactions and behaviors. Various approaches and technologies can be used to collect data, and mixed approaches may provide richer data. Using technology to understand and improve social networks of older adults may help to improve infection control and reduce social isolation, especially during the COVID-19 era; however, there is a lack of implementation science and clinical care practices to address this need. The challenges imposed by COVID-19 further remind researchers and clinicians that well-being and care management is a complex social and health issue requiring multidisciplinary collaboration and problem-solving. Future studies should leverage current work related to COVID-19 and technology to evaluate how the necessity of maintaining physical distancing can be balanced with improvement in the social well-being of older adults via social networks. Future studies should also consider commercial products that target older adults as major user groups to provide a comprehensive review of technologies used to measure social networks.

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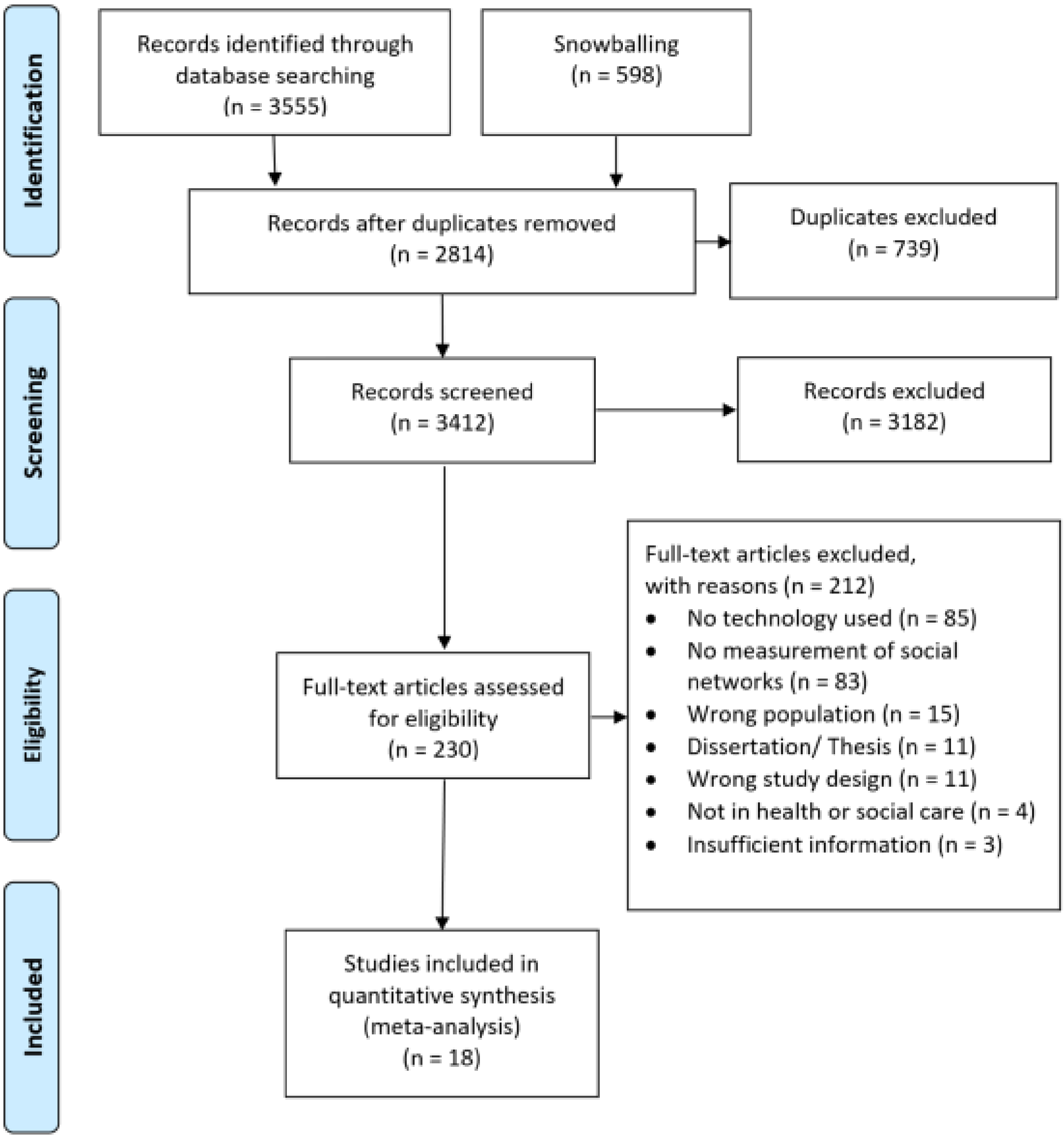

Figure 1. *PRISMA flow diagram of study selection and inclusion process*

Table 1. *Overview of Technologies Included in Review*

Category of Technology	Technologies	Measures	Advantages	Disadvantages
Environment based	• Passive infrared sensors • Passive radio frequency sensors • Internet of Things [a] • Video (camera) and audio recordings	Room occupancy, movement, stage of devices, activity time	• Can cover the entire room • Well-established technology • Once installed, minimal maintenance needed • Easy to deploy • Not obstructed by clothing • Offers room-level accuracy • Easy to obtain status of device use	• May not have good resolution • May not detect multiple people in the room • May not be able to distinguish between different people • Systems that track motion may be "tricked" by animals (vs. humans) • May need to hardwire sensors to install • Need to have devices with built-in sensors or can be modified • Sensors that need to be connected to networks can have security risks
Person based	Camera in smartphone	Pictures of QR codes or the person/ people	• Customizable • Can be easily adopted • QR codes are well established and easy to create	• Needs programing • Camera can be blocked by clothing • Camera can be damaged • Smartphone size is large and cumbersome
	GPS in smartphone or smartwatch	Location, proximity	• Well established and easy to care for • People are familiar with it	• Requires custom programing to use • GPS does not work well indoors • Resolution of GPS is limited to 16-foot radius in open space
	Accelerometer and heart rate detector in smartwatch	Activity level and time	• Well established and easy to use • People are familiar with it • Customizable	• May require custom programming to use • May only be validated in a young population
	Wearable face-to-face proximity sensors: • Infrared sensor embedded name badge • Active radio-frequency identification proximity sensors	Face-to-face proximity between people	• Commercially available device • Directional • Real-time • Able to distinguish individuals • Only detects face-to-face encounters • High resolution indoors	• Short battery life may result in loss of data • Only measures when sensors are worn • Only detects people wearing the sensors • Clothing or improper position may obscure the transmission for infrared sensors, but not a limitation for active radio-frequency identification proximity sensors
	Wearable proximity sensors: low-power radio frequency proximity-sensors	Proximity between people	• Commercially available device • Real-time • Able to distinguish individuals • High resolution indoors	• Not directional and unable to distinguish between individuals in face-to-face encounters; therefore, may not be appropriate for interaction • Short battery life may result in loss of data • Only measures when sensors are worn • Only detects people wearing the sensors
Data based	• Extract from existing services • Call and message logs, social network app	Frequency and duration of calls, status, messages, or posts	• Retrospective • Easy to detect communication patterns • Directional	• Limited to what is available • Limited accessibility to data
	Custom-developed platforms: web- or	Proximity between people	Tailorable to meet study purposes	Costly

Category of Technology	Technologies	Measures	Advantages	Disadvantages
	phone-based social network mapping tool			

Note. QR = quick response; GPS = Global Positioning System.

[a] Internet of things is a system of interrelated devices, such as temperature sensors, light sensors, door sensors, and analog sensors embedded in things or in the house, that can connect and exchange data with each other.

Table 2. *Main Characteristics of the Included Studies*						
Study, Country	**Purposes**	**Sample**	**Setting**	**Category of Technology**	**Design**	**Results**
Bilbao et al. (2016), England and Belgium	To test the feasibility of the Social Networks for Older adults to Promote an Active Life system that promotes older adults' social connections	Community-dwelling older adults and caregivers (n=NR, age=NR) of 4 households	Community: private homes	Environment-based	Field-based feasibility and computer simulation	The simulated intervention was successful in increasing older adults' network size and average network degree and decreasing the number of connected components.
Burns et al. (2014), United Kingdom	To evaluate the usability of a technology system aimed to improve the length of homestay and independence of people with dementia	Healthy volunteers (n=6, age range=24-46)	Community: not specified	Person-based	Field-based feasibility	MiLifeCam recognition system was able to identify all social interactions with known individuals and to capture life-logging data in the form of images and location.
Campos et al. (2014), Mexico	To develop a predictive model that can be easily implemented in a computer system to determine social isolation in older adults	Community-dwelling older adults (n=144, age range=60-89, mean age=68.2)	Community: private homes	Environment-based and person-based	Observational	A predictive model of social isolation in older adults was developed.
Chen et al. (2007), United States	To test the feasibility and accuracy of using multiple sensors for detecting social interactions between older adults and their caregivers in a nursing home	Nursing home residents and their caregivers (n=NR, age=NR)	Residential long-term care: a skilled nursing home	Environment-based	Field-based feasibility	• Complex models were less accurate, and the decision tree model had an accuracy of 99%. • Logitboost models (a boosting algorithm in machine learning) and support vector machine and showed robustness against noises.
Cook et al. (2010), United States	To evaluate the accuracy of computational algorithms to detect social interactions using sensor data in smart environments	Undergraduate student volunteers (n=2, age=NR)	Lab: smart environment testbeds	Environment-based	Lab-based feasibility	The hidden Markov Chain model reached 90% accuracy in determining social activities with people.
Duval et al. (2018), France	To describe inter-individual contacts in hospital wards using proximity sensors and to explore factors associated with high contacts to inform infectious disease control	Geriatric patients (n=136, age=NR) and hospital staff (n=174, age=NR)	Hospital: geriatric rehabilitation	Person-based	Longitudinal observational	• Some physicians and nurses were likely to have higher contacts with patients than other providers. • Patients interact more frequently and spent more time with one another than with providers.
Kennedy et al. (2016), United Kingdom	To evaluate whether the awareness of social networks can improve social integration and the implementation of a social network-centered self-management intervention	Community-dwelling older adults with type 2 diabetes (n=15, age range=43-73)	Community: at the convenience of the participants	Data-based: using custom-designed platforms	Longitudinal case study	A social network-centered self-management intervention (called Generating Engagement in Network Involvement) effectively engaged participants in new activities and expanded their social networks.

Masumoto et al. (2016), Japan	To evaluate face-to-face interactions and community involvement among older adults in an exercise program using wearable sensors	Community-dwelling older adults ≥ 60 (n=27, mean age=73.4)	Community: not specified	Person-based	Field-based feasibility	• The participants were interested in interacting with residents and being involved in the community. • The frequency of face-to-face interactions increased.
Mo et al. (2018), Unspecified	To explore usage patterns of older adult Facebook users and how their diverse characteristics influence their usage and social circles	Older adults (n=2126, age range= 60-89)	Online community	Data-based: using existing services	Observational	• Personality profiling can help predict SNS usage behaviors. • Older adults who used SNS tended to build small social circles (e.g., family relationships).
Muller et al. (2013), UK	To evaluate new low-power proximity-sensors for tracking and measuring care interaction patterns to support discussions on care practices	Older adult residents (n= 9, age=NR) and formal caregivers (n=10, age=NR)	Residential long-term care: a care home specialized in dementia care	Person-based	Observational	• 44% of caregivers' activities could be matched to care tasks and interactions with residents. • The data were useful in starting discussions between caregivers and triggered collaborative reflection.
Peter et al. (2013), Greece, Spain, and Sweden	To evaluate a technologically mediated social network system to assist older adults living independently in their own homes to interact with their social network and improve their quality of life	Community-dwelling older adults: user group (n=29, mean age= 74, range=65-80); control group (n=18, mean age =75, range=68-91)	Community: private homes	Environment-based	Randomized controlled trial	• The technologically-mediated social network system were well adopted by older adults • Use of this system had positive effects on the users' mental state, compared to the control group without the technology.
Pfeil & Zaphiris (2009), UK	To investigate the social network of an empathic online community for older adults	Older adults (n=47, age=NR)	Online community	Data-based: using custom-designed platforms	Observational	• Participants were more connected in the social networks on empathic communication compared to non-empathic communication. • The empathic communication was linked to the social network structure
Pfeil et al. (2011), UK	To examine an online support community for older people and to identify different online social roles	Older adults (n=29, age=NR)	Online community	Data-based: using custom-designed platforms	A multi-methods study	• Six social roles were identified. • The structural positions of online community members were associated with the type of content they posted.
Quintana et al. (2019), USA	To investigate the feasibility of a web-based tool (online platform) for care coordination for older adults and their caregivers	Older adults (n=157, mean age= 75.5), family and formal caregivers (n= 128, mean age=56.6)	Community: retirement and continuing care communities	Data-based: using custom-designed platforms	Field-based feasibility	• It was feasible to establish an online platform for older adults and their families for information exchange and care coordination. • Most care coordination networks existed as dyad pairs.

Rebola et al. (2013), US	To examine the feasibility of an automated behavioral mapping surveillance system designed to monitor interactions among older adults in retirement communities	Older adults (n=NR, aged≥62)	Community: retirement communities	Environment-based	Experimental pilot study using field-based and lab-based simulation	Social interactions among older adults were detected using video cameras.
Uddin et al. (2015), Australia	To develop a framework that uses claims data and social network analysis to understand health care coordination and collaboration	Patients with hospital admissions for total hip replacement (n=2229, age=NR)	Hospital	Data based: using existing platforms	Observational	• The framework helped extract and explore care coordination networks using health insurance claims data. • Degree centrality and tie strength were positively correlated with length of stay. • Fewer triangle structures in networks predicted more effective collaboration.
Vanhems et al. (2013), France	To detect patterns of close-range interactions between individuals to better understand infection spread	Geriatric patients (n=29, age=NR) and health care workers (n=46, age=NR)	Hospital: a geriatric unit of a hospital	Person-based	Longitudinal observational	• Contact numbers and duration varied greatly across individuals and over time. • Six providers were potential "super-contactors' who had a larger number and duration of contacts than average.
Yu et al. (2015), China	To facilitate medication adherence by combining ubiquitous sensors and social networking intervention via a mobile application	Older adults (n=5, aged≥60)	Community: private homes	Environment-based and data based: using custom-designed platforms	Comparative experimental	A socialized prompting system enhanced the medication adherence of the older adults.

Note. NR = Not reported, SNS = Social Network Sites