

The Application of Robots and Digital Health in Elderly Care: A Bibliometric Analysis of 20 Years of Research Landscape and Frontier Evolution

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Abstract. The aging of the global population has put a huge strain on elderly care systems everywhere, and that's why robotics and digital health technologies are now being looked at as ways to tackle some of the toughest problems in geriatric care. What's been missing, though, is a clear, numbers-based picture of how this whole interdisciplinary field has taken shape and where it's heading. Our study aimed to fill that gap by pulling together and analyzing 4,646 publications from the Web of Science Core Collection, covering the years 2005 to 2025, with the help of the CiteSpace visualization tool. We mapped out how the volume of papers has grown, which journals matter most, and what the collaboration networks look like at the author, institution, and country levels. It turns out that the research community is pretty fragmented when you look at who works directly with whom, but there's a strong shared knowledge base linking everyone together. When we tracked the key themes over time, three clear stages stood out: early days spent on basic assistive devices, a middle period that brought intelligent monitoring and evidence-based practice into the picture, and a more recent wave of work zooming in on human-robot interaction and psychosocial support. We also dug into the field's intellectual foundations and spotted the emerging frontiers—things like using social robots to ease loneliness, the ongoing struggle with technology acceptance, and the push to standardize how evidence gets synthesized. By laying out this big-picture, data-driven map of the field, we hope to give researchers, clinicians, and policymakers a handy reference for planning future studies and strategies in technology-assisted elderly care.

Keywords: robotics, digital health, elderly care, bibliometric analysis

1. Introduction

The world's population is getting older at a speed we've never dealt with before. If the World Health Organization (WHO) projections hold, the number of people aged 60 and above is going to hit 2.1 billion by 2050, and those who are 80 or older will triple between 2020 and 2050, reaching 426 million [1]. A demographic swing this big is putting serious pressure on care systems across the globe, creating an urgent call for fresh ideas that can work at scale and fit alongside the care that human hands have always provided. That's the backdrop against which robotics and digital health

technologies have stepped into the spotlight, offering promising ways to deal with everything from helping with daily tasks and keeping health monitored around the clock, all the way to supporting memory and cutting down on loneliness [2-4].

The whole mix of robotics, artificial intelligence, and digital health in the context of elderly care has come a long way—from a few scattered ideas about assistive gadgets at the turn of the century to a lively, interdisciplinary field that keeps expanding. Back in the early 2000s, most of the work centered on basic aids and simple forms of remote monitoring, but once machine learning, deep learning, and activity recognition got woven into the picture, the possibilities for non-invasive, smart, and personalized care really opened up [5, 6]. Lately, the spotlight has shifted toward human-robot interaction, digital health platforms, and socially assistive robots, which is a sign that the whole enterprise is moving past the "look what this tech can do" phase and into one that's shaped more by evidence about what older adults truly want and need [7, 8]. The growing pile of literature now cuts across medical informatics, geriatrics, computer science, and public health—a clear signal that the field has matured and that technology-assisted elderly care is being taken seriously as something with real clinical and social weight [9, 10].

Even with all that activity, we still haven't had a proper quantitative look at the overall intellectual landscape and the path this field has followed over time. Narrative reviews are helpful, sure, but they can only go so far when it comes to capturing the structural twists, thematic turns, and emerging edges of a fast-moving interdisciplinary domain. Bibliometric analysis, especially when you pair it with visualization tools like CiteSpace, gives you a powerful, data-driven way to fill that gap, using network and burst analysis on big batches of literature to spot influential players, track research hotspots as they shift, and pinpoint what's coming next [11, 12]. That's exactly what we set out to do here.

2. Data and methods

2.1. Data collection

Data were retrieved from the Web of Science Core Collection, covering SCI-EXPANDED, SSCI, A&HCI, CPCI-S, CPCI-SSH, BKCI-S, BKCI-SSH, ESCI, CCR-EXPANDED, and IC. A topic search was conducted on December 31, 2025, using the strategy: TS=("robotics" OR "robot" OR "digital health" OR "digital technology" OR "intelligent technology") AND TS=("elderly care" OR "aged care" OR "geriatric care" OR "older adults" OR "elderly people" OR "seniors"), limited to articles and reviews published 2005–2025. The initial search yielded 12,689 records. After removing 4,429 duplicates indexed in multiple sub-databases, 8,260 unique records remained. Title and abstract screening excluded 3,614 publications for reasons including: industrial or surgical robotics with no elderly care application (n=1,482), digital health interventions without a geriatric-specific component (n=1,327), and non-research items misclassified as articles or reviews (n=805). Ultimately, 4,646 publications were retained for analysis. The screening is detailed in the PRISMA flow diagram (Figure 1). Each downloaded record included authors, title, abstract, descriptors, and identifiers.

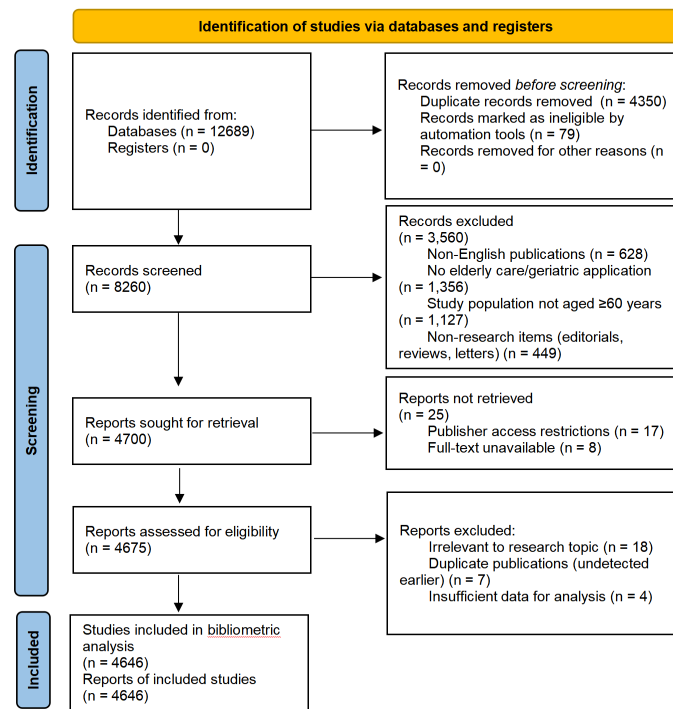


Figure 1. PRISMA flow diagram of the publication screening process

2.2. Inclusion and exclusion criteria

Inclusion criteria were: peer-reviewed original articles and reviews on robotics and digital health in elderly care, published in English. Exclusion criteria: duplicate publications and those whose titles and abstracts showed no relevance to the topic.

3. Results

3.1. Publication trends

From 2005 to 2025, 4,646 publications were retained after deduplication and screening. Annual output remained low before 2010 (fewer than 800 cumulative publications), then entered a phase of rapid growth, peaking in 2024 with 592 papers. The cumulative total of 4,671 is highly consistent with the retained 4,646. The earliest studies, appearing in 2005, centered on "assistive technology." Figure 2 shows the trend.

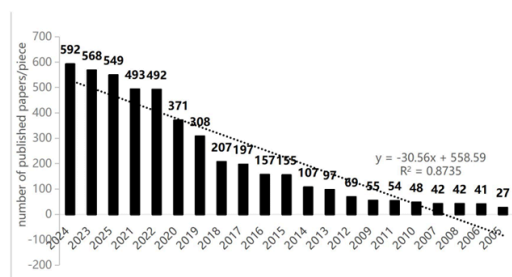


Figure 2. Annual publication trends of robotics and digital health for elderly care research (2005-2025)

3.2. Journal distribution

Research is published across journals in medical informatics, geriatrics, computer science, and public health. Table 1 lists the top 10 most frequently co-cited journals. Journal of Medical Internet Research (JMIR) leads with 1,010 co-citations, followed by PLOS ONE (951), Journal of the American Geriatrics Society (744), and International Journal of Environmental Research and Public Health (718). Impact factors (2024) of these top journals range from 2.3 to 88.5.

Table 1. Top 10 most frequently co-cited journals in robotics and digital health for elderly care (2005-2025)

serial number	Count	Centrality	Cited Journals
1	1010	0.11	J MED INTERNET RES
2	951	0.01	PLOS ONE
3	744	0.95	J AM GERIATR SOC
4	718	0.02	INT J ENV RES PUB HE
5	708	0.66	JAMA-J AM MED ASSOC
6	675	0	BMJ OPEN
7	673	0.08	BMJ-BRIT MED J
8	671	0.96	LANCET
9	626	0.04	BMC GERIATR
10	620	0.09	SENSORS-BASEL
11	616	0	J AM MED DIR ASSOC
12	610	0.03	INT J MED INFORM

3.3. Co-authorship analysis

The co-authorship network (Figure 3) contains 263 nodes and 198 links, with a very low density of 0.0057. Modularity Q is 0.7977 and the weighted mean silhouette is 0.9364, indicating a strongly modular structure where authors cluster into internally cohesive but externally isolated groups. Direct collaboration remains mostly within small, stable teams. The most productive author is David Bogataj (12 papers on frailty assessment and fall risk management using digital health), followed by Daisuke Chugo (12 papers) and Naonori Kodate (11 papers), each leading separate clusters.

Despite sparse direct collaboration, the cited author co-citation network (N=397, E=440) and citing author network (N=448, E=542) both show giant connected components exceeding 84% of nodes. This reveals a latent intellectual community: teams work as isolated "academic islands" in co-authorship but share a highly integrated knowledge base, with authors like WHO, Broadbent E, Davis FD, and Folstein MF [13] serving as knowledge bridges. In short, the landscape is "locally dense, globally sparse" in direct ties but strongly connected through shared intellectual foundations.

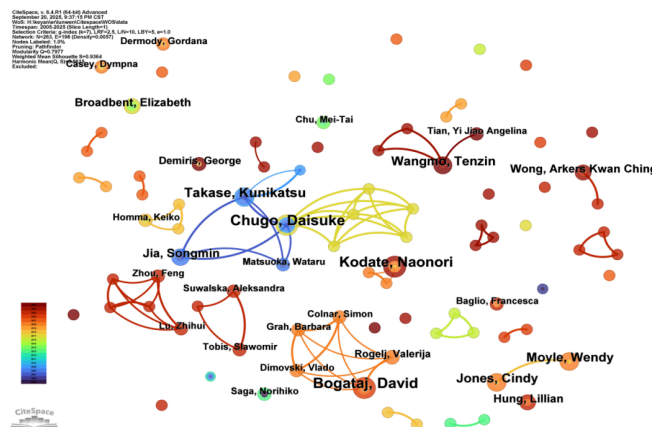


Figure 3. Author co-authorship network of robotics and digital health for elderly care research (2005-2025)

3.4. Co-institute analysis

Harvard University led in publication volume (85 papers), followed by the University of California System (76) and the University of Toronto (75). The co-institute network (Figure 4) has 230 nodes and 208 links (density 0.0079), with the largest connected component covering 60% of institutions. Six institutions showed betweenness centrality ≥ 0.1 , with Harvard Medical School (0.37) having the highest bridging capacity, followed by the University System of Ohio (0.21), University of London (0.14), University of California System (0.15), Harvard University Medical Affiliates (0.13), and University of Toronto (0.12). These hubs connect research teams across North America, Asia, and Europe.

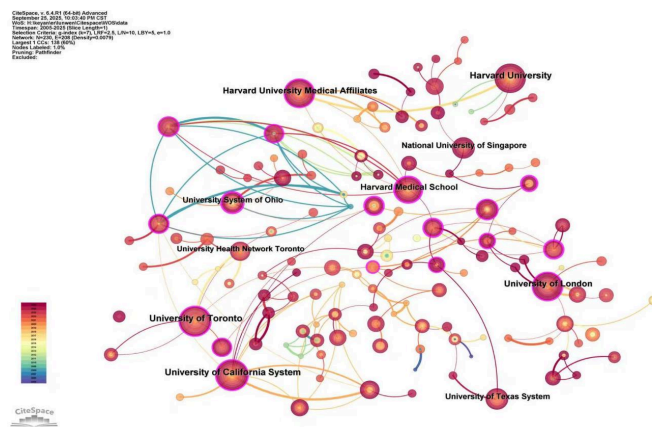


Figure 4. Institutional co-authorship network of robotics and digital health for elderly care research (2005-2025)

3.5. Co-country analysis

At the country level (Figure 5), the United States, China, and the United Kingdom are the top three producers, with 1,008, 682, and 431 publications respectively, and maintain strong collaborative ties with each other and with many other regions.

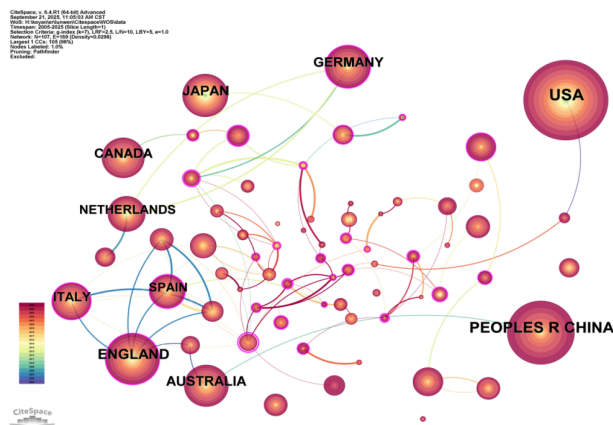


Figure 5. Country co-authorship network of robotics and digital health for elderly care research (2005-2025)

3.6. Keyword co-occurrence analysis

Keyword co-occurrence (Figure 6) shows "older adults" as the most frequent term (620 occurrences), followed by "care," "people," "health," and "technology." Keywords with high betweenness centrality include "health" and "care." The time-zone view (Figure 7) reveals a three-stage thematic evolution.

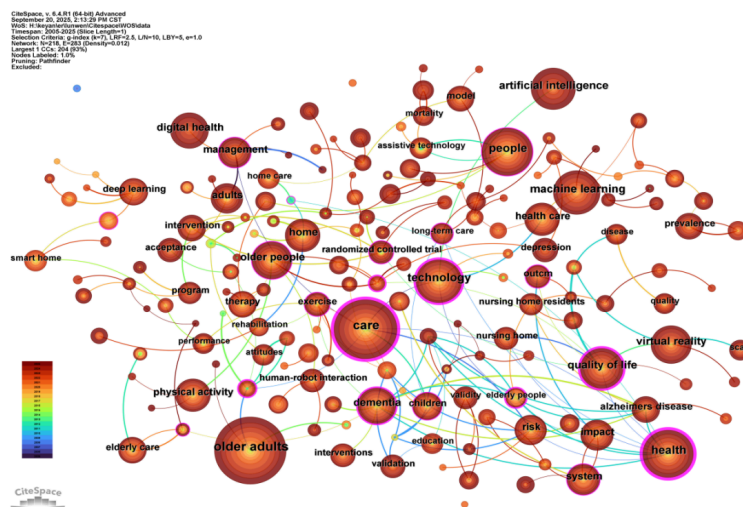
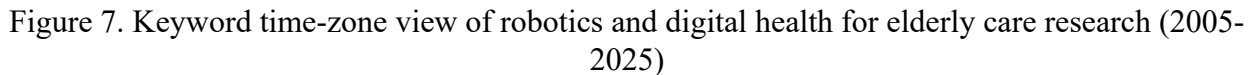


Figure 6. Keyword co-occurrence network of robotics and digital health for elderly care research (2005-2025)



3.7. Publication co-citation analysis

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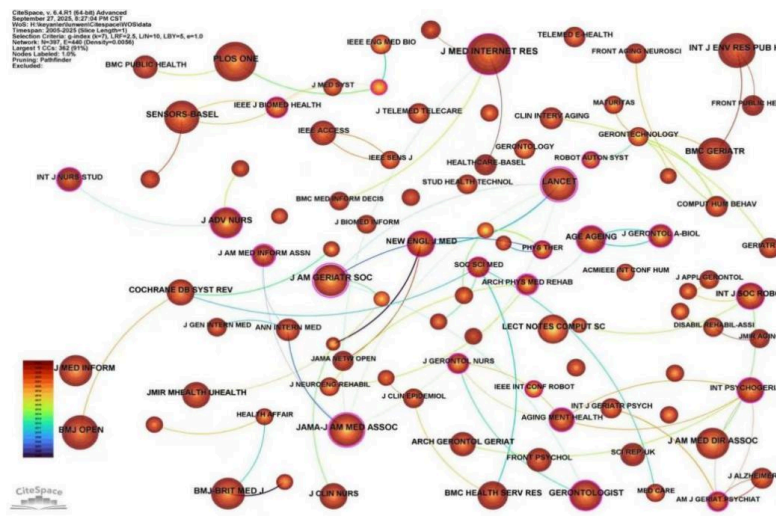


Figure 8. Document co-citation network of robotics and digital health for elderly care research (2005-2025)

Table 2. Keyword clustering results of robotics and digital health for elderly care research (2005-2025)

ClusterID	Size	Silhouette	mean(Year)	Label(LLR)
0	19	0.903	2013	impact(33.24,1.0E-4);system(33.24,1.0E-4);prevalence(24.5,1.0E-4);risk factors(20.29,1.0E-4);older adults(18.45,1.0E-4)
1	19	0.967	2012	care(41.92,1.0E-4);prevention(28.88,1.0E-4);risk(22.05,1.0E-4);paediatrics(14.43,0.001);family caregivers(13.38,0.001)
2	19	0.932	2017	elderly care(42.45,1.0E-4); randomized controlled trial(23.03,1.0E-4);program(21.43,1.0E-4);mobile health(16.44,1.0E-4);mhealth(15.3, 1.0E-4)
3	18	1	2017	older people(68.68,1.0E-4);human-robot interaction(30.55,1.0E-4);physical activity(29.8,1.0E-4);older adult(27.05,1.0E-4);social isolation(22.34,1.0E-4)
4	17	0.884	2014	nursing students(73.54,1.0E-4);older adults(64.26,1.0E-4);nursing education(38.94,1.0E-4);digital technology(27.83,1.0E-4);experiences(21.45,1.0E-4)
5	17	0.977	2015	mild cognitive impairment(62.13,1.0E-4);alzheimers disease(47.43,1.0E-4);dementia(41.19,1.0E-4);remote monitoring(27.35,1.0E-4);cognitive impairment(21.17,1.0E-4)
6	16	0.932	2014	assistive technology(40.69,1.0E-4);social robots(33.35, 1.0E-4);therapy(26.29,1.0E-4);people(17.3,1.0E-4);risk assessment(10.51,0.005)
7	15	0.939	2010	machine learning(176.63,1.0E-4);artificial intelligence(161.48,1.0E-4);prediction model (28.83,1.0E-4);natural language processing(23.15,1.0E-4);medical informatics(22.25,1.0E-4)
8	14	0.968	2017	deep learning(126.6,1.0E-4); activity recognition(84.97,1.0E-4);fall detection(60.38, 1.0E-4);smart home(47.35,1.0E-4);feature extraction(33.82,1.0E-4)
9	14	0.874	2019	nursing homes(59.44,1.0E-4);long-term care(36.01,1.0E-4);qualitative research (33.46,1.0E-4);primary care(20.07,1.0E-4);virtual reality(18.51,1.0E-4)

Table 2. (continued)

10	13	0.875	2013	home care(36.51,1.0E-4);trials(17.27,1.0E-4);systematic review(16.83,1.0E-4);care robot(13.82,0.001);machine learning(12.47,0.001)
11	12	0.932	2012	virtual reality(112.39,1.0E-4); quality of life(41.93,1.0E-4); nursing home(35.56,1.0E-4); pediatric(20.17,1.0E-4);anxiety(17.96,1.0E-4)
12	11	0.985	2014	digital health(93.07,1.0E-4);heart failure(30.54,1.0E-4); technology adoption(14.12,0.001);adults(11.71,0.001); dementia(11.25,0.001)

3.8. Citation bursts

Table 3 lists the top 10 references with the strongest citation bursts. Page MJ et al. [14] (PRISMA update) is the most cited, with 71 citations, reflecting the field's emphasis on rigorous evidence synthesis. Moyle W et al. [4] on telepresence robots for dementia care ranks fifth with 35 citations, its burst sustained from 2019 to 2025, amplified by COVID-19. The earliest bursts include Braun and Clarke [5], Venkatesh et al. [15], and Davis [16]; mid-period bursts include Wada K [17], Liberati et al. [14], and Heerink et al. [6]; the most recent and continuing bursts feature Robinson et al. [3], Broadbent et al. [2], WHO [1], Alzheimer's Disease International [18], and Moyle et al. [4]. Early bursts laid the theoretical and methodological norms, while the active bursts since 2014 mark the current research frontiers.

Table 3. Top 10 references with the strongest citation bursts in robotics and digital health for elderly care (2005-2025)

serial number	Count	Centrality	Cited References
1	71	0	Page MJ, 2021, BMJ-BRIT MED J, V372, P0, DOI 10.1136/bmj.n160
2	51	0.02	Abdi J, 2018, BMJ OPEN, V8, P0, DOI 10.1136/bmjopen-2017-018815
3	43	0.01	Tricco AC, 2018, ANN INTERN MED, V169, P467, DOI 10.7326/M18-0850
4	38	0.03	Pu LH, 2019, GERONTOLOGIST, V59, PE37, DOI 10.1093/geront/gny046
5	35	0	Moyle W, 2017, J AM MED DIR ASSOC, V18, P766, DOI 10.1016/j.jamda.2017.03.018
6	33	0.01	Melkas H, 2020, INT J MED INFORM, V134, P0, DOI 10.1016/j.ijmedinf.2019.104041
7	28	0.06	Papadopoulos I, 2020, BMJ OPEN, V10, P0, DOI 10.1136/bmjopen-2019-033096
8	24	0.03	Liang A, 2017, J AM MED DIR ASSOC, V18, P871, DOI 10.1016/j.jamda.2017.05.019
9	24	0.12	Petersen S, 2017, J ALZHEIMERS DIS, V55, P569, DOI 10.3233/JAD-160703
10	22	0.01	Fischinger D, 2016, ROBOT AUTON SYST, V75, P60, DOI 10.1016/j.robot.2014.09.029

4. Discussion

4.1. Overall trends and driving factors

Looking at how the number of publications has climbed over the years, it's easy to see the field maturing step by step, with each big jump tied to something concrete. The slow buildup before 2010 was all about getting a feel for what assistive devices could do on their own—there wasn't much tying them together into any kind of connected care system. After 2010, though, things started to speed up, and there were a few reasons for that: the global population was aging faster, which created a real hunger for care solutions that could be scaled up, while advances in AI—machine learning, and then deep learning a few years later—gave researchers a new technical toolbox to work with. More funding and the wider digital shake-up of healthcare helped too. One moment that really stands out came around 2013, when "randomized controlled trial" started showing up as a citation burst. That's when the field began to move past just showing something could be done and started asking whether it actually worked in a rigorous, evidence-backed way. The PRISMA Statement [13] had already set the stage for better reviews, so the push for both strong primary studies and careful evidence syntheses became a defining feature. Then, when "deep learning" and "activity recognition" popped up as hot keywords in 2017, it was clear that a shift had happened toward monitoring that could run quietly in the background, without needing the person to do anything, which lines up nicely with the trend toward proactive, person-centered care.

4.2. Key journals and collaborative networks

The journal list tells a story of its own. JMIR sitting at the top makes sense—it's a natural home for digital health work—while PLOS ONE pulls in a wide mix of studies thanks to its open-access model. The geriatrics and public health angles are well covered by the Journal of the American Geriatrics Society and the International Journal of Environmental Research and Public Health, and the fact that the impact factors stretch from the low single digits up to nearly 90 shows the field has gained a foothold in journals of all tiers. As for the people doing the work, the collaboration network is pretty fragmented: most teams stick to themselves, and you don't see a lot of cross-group co-authorship. David Bogataj, for instance, has built a steady line of research on using digital health to assess frailty and manage fall risk, showing how personalized interventions can be built on multidimensional assessments [19]. At the institutional level, places like Harvard Medical School, the University System of Ohio, and the University of London act as hubs, bridging groups across continents and helping to build consensus on methods and standards—the kind of behind-the-scenes work that makes global dissemination of these technologies possible [20].

4.3. Evolution of research hotspots

The three stages we saw in the keyword analysis really capture a deeper change in what's driving the field. Early on, the vocabulary was broad and fuzzy, which is what you'd expect when people are still figuring out the boundaries of the conversation. The middle period brought two big forces together: machine learning gave researchers ways to handle the messiness of geriatric data, while the turn toward RCTs showed a willingness to subject these technologies to the same evidentiary standards as any other medical intervention. That was a big deal—it redefined what counted as credible. In the most recent stage, the conversation has turned toward things like "social isolation" and "human-robot interaction," which means the question isn't just "can we build it?" anymore but

"does it actually make life better for older adults on their own terms?" Psychosocial outcomes have moved from the edges to the center, and that means studies now have to think about user-centered design from the start and track things like quality of life as seriously as any technical metric.

4.4. Intellectual base and emerging frontiers

The work that gets cited most often in this field isn't a random collection of papers—it forms a set of pillars that hold the whole thing up. Moyle et al. [4] showed that social connectedness could be measured and targeted, which gave later social robot trials a template to follow. Broadbent et al. [2] and Robinson et al. [3] kept hammering home the point that user acceptance, not technical capability, is what makes or breaks real-world deployment—an insight that still shapes how people study technology adoption today. Braun and Clarke's thematic analysis [5] brought a qualitative lens that has helped bridge the gap between what engineers build and what older adults actually experience. And on the policy side, the WHO [1] and Alzheimer's Disease International [18] reports gave these technologies a seat at the table in global healthy aging strategies. Looking ahead, three fronts are especially active: social robots for loneliness, where we need longer follow-ups to see if the benefits stick; technology acceptance, where co-design and attention to age-related usability issues have to be baked in from the start; and the ongoing push for evidence synthesis, which calls for standardized reporting and systematic reviews of the most coherent clusters, like Cluster 3 on human-robot interaction and Cluster 5 on cognitive decline. Multimodal data integration and equity in access are cross-cutting issues that will need attention too [21, 22].

4.5. Limitations and future directions

A few things about this study should be kept in mind. We only pulled records from the Web of Science Core Collection, which means work in Scopus, PubMed, or non-English outlets might be underrepresented, tilting the view a bit toward Western research. The network pictures that CiteSpace generates are also sensitive to the parameters you choose, and there's always some subjectivity in how clusters and bursts get interpreted. To get a fuller picture down the road, it would be smart to bring in multiple databases and to focus systematic review efforts on those high-consistency clusters we mentioned, while also running more cross-cultural and implementation studies to close the gap between lab innovation and everyday practice.

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