From Ambient Intelligence to Deep Learning a Bibliometric Analysis of Smart Home Technologies for Elderly Care

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Abstract. Aligned with the United Nations Sustainable Development Goals (SDGs), age-friendly smart homes provide a vital technological framework for advancing healthy and sustainable aging. Despite increasing academic focus, a comprehensive informatics-based synthesis of this field is still restricted. This study conducts a systematic bibliometric analysis to evaluate scientific outputs and identify emerging research themes in age-friendly smart home technologies. CiteSpace and additional visualization tools were used to assess 700 pertinent publications (2006–2025) that were found in the Web of Science Core Collection using a keyword-driven search strategy. The results indicate a steady growth in research output, with China, the UK, and the USA identified as the most influential contributors. Sensors and IEEE Access are the main publication venues, while the Centre National de la Recherche Scientifique is the dominant institution, according to key findings. Bibliometric mapping reveals that "Internet of Things" and "Activity Recognition" constitute the core technological foundations. Notably, a significant transition toward advanced artificial intelligence is observed, characterized by recent citation bursts in "Machine Learning" and "Deep Learning." These trends suggest a paradigm shift from basic ambient assisted living toward sophisticated, user-centric AI applications. The study concludes that future research will increasingly emphasize the convergence of AI and smart living informatics, necessitating enhanced international collaboration to bridge the gap between technological innovation and sustainable elderly care.

Keywords: Age-friendly smart homes, Bibliometric analysis, Science mapping, Aging population, Smart living

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1 Introduction

With continuous improvements in living standards and medical conditions, global life expectancy has increased markedly, resulting in rapid population ageing worldwide. With advancing age, functional decline becomes more evident, accompanied by deteriorating physical health and heightened susceptibility to chronic conditions such as cardiovascular diseases, diabetes, dementia, and mobility limitations[1], [2]. Population ageing has emerged as a major global challenge, and promoting healthy and sustainable ageing is a central goal of contemporary gerontology research. Families, societies, and healthcare systems are under a great deal of strain due to the increased healthcare needs of older persons, especially in light of the scarcity of medical resources and the escalating expenses of care [3], [4].

Age-friendly smart homes have been increasingly recognized as an effective technological solution to address these challenges. Rooted in the concepts of intelligent environments and ambient intelligence, age-friendly smart homes include technologies such as the Internet of Things, artificial intelligence, sensors, and data analytics to promote independent living, health monitoring, and safety management for the elderly[5], [6]. By enabling functions such as activity recognition, fall detection, and personalized health services, smart homes can improve quality of life, reduce caregiver burden, and facilitate ageing in place[7].

Moreover, age-friendly smart homes promote the achievement of the United Nations Sustainable Development Goals (SDGs), specifically SDG 3 (Good Health and Well-being) and SDG 11 (Sustainable Cities and Communities), by creating healthy, safe, and inclusive environments for elderly individuals[8], [9]. However, older adults often face barriers related to technology acceptance, usability, and accessibility, which may limit the practical benefits of smart home systems if not adequately addressed[6], [10].

Recent years have witnessed an increasing volume of research into the utilization of smart home technologies for elderly populations. Notwithstanding this swift growth, current research remains disjointed, and a thorough examination of worldwide research trends, key contributors, and nascent themes in age-friendly smart homes is still absent. Bibliometric analysis provides a systematic and quantitative method for delineating the intellectual framework and developmental trajectory of a study domain[9]. This study performs a bibliometric analysis of international research on age-friendly smart homes, utilizing papers listed in the Web of Science Core Collection. This study analyzes publication outputs, countries, institutions, authors, journals, keywords, and citation patterns to identify research hotspots, evolutionary trends, and future directions, offering valuable insights for researchers and policymakers aiming to advance healthy and sustainable aging through smart home technologies.

2 Research Method and Procedures

2.1 Bibliometric Approach

Bibliometric analysis is a quantitative research methodology that investigates the intellectual framework and development of a subject domain utilizing extensive bibliographic databases[11]. This science-mapping technique visualizes relationships across documents, authors, journals, institutions, nations, and keywords using network representations, therefore elucidating patterns of collaboration and theme evolution within a discipline[12], [13]. In contrast to conventional narrative reviews, bibliometric analysis offers a transparent, systematic, and reproducible review procedure based on statistical and mathematical metrics, hence augmenting objectivity and trustworthiness[14]. With the rapid growth in the volume of scientific publications, bibliometric methods have become increasingly important for structuring large bodies of information, identifying major research streams, tracking shifts in disciplinary boundaries, and capturing the overall landscape of a research field[15]. To achieve the objectives of this study, a series of bibliometric analyses will therefore be conducted.

2.2 Analysis Tool

CiteSpace was utilized to conduct a bibliometric analysis. This research utilizes CiteSpace (version 6.4.R1) to conduct a knowledge-graph analysis of the chosen literature. CiteSpace is a Java-based information visualization tool created by Professor Chaomei Chen and his research team at Drexel University, facilitating the identification and visual representation of research fronts, intellectual foundations, and rising trends in scientific disciplines. CiteSpace assists researchers in describing the existing structure of a study topic and inferring likely frontiers and development trajectories from the topology and temporal patterns given by the maps by producing co-citation, co-occurrence, burst detection, and cluster visualizations[16], [17].

Knowledge maps for visualization comprise nodes and connections. Various nodes on a map signify elements such as cited references, institutions, authors, and countries, while the connections between nodes denote linkages of collaboration, co-occurrence, or co-citations. The hue of nodes and lines signifies distinct years. The purple circle signifies centrality. Nodes with high centrality are typically considered critical junctures or focal points within a domain[16], [18], [19].

2.3 Data Collection

A comprehensive bibliometric review was conducted using the Web of Science (WoS) Core Collection, which is widely recognized for its rigorous indexing standards, structured citation data, and extensive coverage of peer-reviewed academic literature. WoS was selected due to its strong citation-tracking functionality and curated metadata, which support advanced bibliometric and science-mapping analyses under transparent and reproducible indexing criteria[20]. In addition, its standardized export format is highly compatible with CiteSpace, enabling consistent co-citation, co-occurrence, burst detection, and clustering analyses.

Following the search strategy summarized in Table 1, the TOPIC field in the Web of Science Core Collection was applied, which searches titles, abstracts, author keywords, and Keywords Plus. To improve transparency and reproducibility, the exact search query used in this study was as follows:

TS=(("age-friendly" OR "old people" OR "elderly" OR "elderly people" OR "aged") AND ("smart home*" OR "intelligent home*" OR "smart furniture*" OR "intelligent furniture*"))

The first group of terms was used to capture ageing-related populations, while the second group was used to identify smart-home and intelligent-living technologies. The search was limited to peer-reviewed articles and review articles published in English between January 1, 2006 and December 20, 2025. Although relevant studies may exist in other languages, restricting the dataset to English-language publications enhanced international comparability and analytical consistency.

Table 1. Search strings used in the Web of Science (WoS) database.

Parameter	**Description**
Database	Web of Science (WoS) Core Collection
Search Field	"TOPIC" (searching in titles, abstracts, author keywords, and Keywords Plus)
Search Terms	("age-friendly" OR "old people" OR "elderly" OR "elderly people" OR "aged") AND("smart home*" OR "intelligent home*" OR "smart furniture*" OR "intelligent furniture*")
Publication Data	January 1, 2006 to December 20, 2025
Document Types	Article or Review Article
Language	English
Retrieved Date	December 20, 2025

The data were exported as unformatted text files (complete records and referenced citations). Following deduplication and formatting with CiteSpace 6.4.R1, a total of 700 legitimate publications were ultimately preserved for study.

2.4 Data Analysis

This study utilizes CiteSpace (version 6.4.R1) as the principal analytical instrument to thoroughly analyze the existing landscape of global research on age-friendly smart homes. Initially, pertinent material was meticulously extracted from the Web of Science database, exported in plain text format, and later loaded into CiteSpace. The analysis encompasses the timeframe from January 2006 to December 2025. To enhance analytical accuracy and temporal resolution, a time slice of one year was applied. Key parameters—including term source (all selected), node types (selected individually per analysis), selection criteria (g-index, k=12), pruning methods (pathfinding and pruning sliced networks), and visualization mode (cluster view-static with merged network display)—were configured accordingly (detailed settings are provided in Table 2).

Table 2. Configuration and parameter settings used in the CiteSpace analysis.

Parameter	**Setting**
Software	CiteSpace (Version 6.4.R1)
Time Span	January 2006 to December 2025
Years Per Slice	1
Node Types	Author, Institution, Country, Keyword, Reference
Selection Criteria	g-index (k = 12)
Pruning	Pathfinding; Pruning sliced networks
Visualization	cluster view-static, show merged network

This is a comprehensive evaluation of the research methodology. An examination of annual publications was performed to ascertain temporal trends and the general expansion of research in the field. An analysis of the global distribution of contributing countries and institutions was conducted to identify significant geographic patterns and prominent research groups.The publication productivity and co-citation networks of journals were analyzed to determine the principal publications and disciplinary foundations of age-friendly smart home research. Subsequently, collaboration patterns and scholarly influence were examined by co-authorship and author co-citation analyses, emphasizing prominent scholars and significant academic contributors within the subject.

To elucidate the intellectual foundation of the research topic, a reference co-citation analysis was conducted to identify highly significant publications and seminal works based on citation frequency and centrality metrics.Ultimately, keyword-based techniques, such as co-occurrence, clustering, and citation burst detection, were utilized to investigate research hotspots, thematic frameworks, and developing trends in age-friendly smart home research. Keyword co-occurrence analysis reveals relationships among core research topics, while clustering analysis illustrates the internal structure and evolutionary trajectories of thematic areas over time.

Although CiteSpace provides effective macro-level visualization and quantitative insights, bibliometric results were further complemented by manual reading and comparative analysis to enhance interpretability and contextual understanding. This integrated approach ensures a robust and systematic assessment of global research patterns and developments in age-friendly smart home studies.

3 Results and Analysis

3.1 Analysis of Publication Outputs

As shown in Figure 1, the distribution of research literatures on age-friendly smart homes from 2006 to 2025 reveals a clear growth trajectory. During 2006–2012, publication output was limited, indicating an initial exploratory stage. From 2013 to 2017, the number of studies increased steadily, reflecting rising scholarly interest in this field. A rapid expansion occurred after 2018, with publications peaking in 2020, suggesting accelerated development driven by technological advances and population ageing. Although minor fluctuations are observed between 2021 and 2025, the overall publication volume remains high. This pattern indicates that research on age-friendly smart homes has entered a stable and mature phase with sustained academic attention.

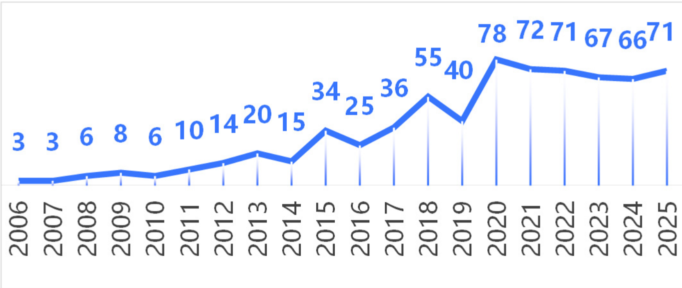

Fig. 1. Annual distribution of publications on age-friendly smart home research (2006–2025).

3.2 Analysis of Country and Institution

Generating the country map using CiteSpace resulted in 72 nodes and 98 links (Figure 2). Overall, 700 publications were produced by scholars from 72 countries. China emerged as the most influential contributor, while the United Kingdom, the United States, South Korea, Australia, and several European and Asian countries formed a second tier of highly active research hubs, reflecting a diversified yet regionally concentrated global research landscape.

Fig. 2. Global distribution of countries conducting research on age-friendly smart homes (2006–2025).

The institution map comprised 239 nodes and 208 links (Figure 3 and Table 3). The publications were distributed across 239 institutions, with the top ten being Centre National de la Recherche Scientifique (15), Nanjing Forestry University (13), Communaute Universite Grenoble Alpes (9), Air University Islamabad (9), Prince Sattam Bin

Abdulaziz University (9), Nottingham Trent University (8), Kyung Hee University (8), Massey University (7), Universite Grenoble Alpes (6), and Chinese Academy of Sciences (6). Analysis of publication volume highlights China and Centre National de la Recherche Scientifique as the leading country and institution.

Centre National de la Recherche Scientifique is a leading research institution in smart home technologies for elderly care. It develops sensor-based monitoring systems, activity recognition algorithms, and voice interfaces to support independent living and healthcare applications through computational methods and wireless networks[21], [22], [23].

Nanjing Forestry University focuses on age-friendly smart home interface design, employing eye-tracking and EEG methods to optimize interaction performance for elderly users, with particular emphasis on smart furniture and recreational system usability[24], [25], [26], [27], [28].

Communaute Universite Grenoble Alpes pioneers in health smart home technologies, developing SVM-based activity classification, voice interfaces, and wearable monitoring systems for elderly care, with strong focus on machine learning and sensor fusion applications[22], [29], [30], [31], [32].

Table 3. Top 10 productive countries and institutions in age-friendly smart home research (2006–2025).

Ranking	**Publications**	**Country**	**Ranking**	**Publications**	**Institution**
1	179	China	1	15	Centre National de la Recherche Scientifique
2	71	United Kingdom	2	13	Nanjing Forestry University
3	64	USA	3	9	Communaute Universite Grenoble Alpes
4	60	South Korea	4	9	Air University Islamabad
5	43	Australia	5	9	Prince Sattam Bin Abdulaziz University
6	42	France	6	8	Nottingham Trent University
7	40	Saudi Arabia	7	8	Kyung Hee University
8	37	Canada	8	7	Massey University
9	36	Spain	9	6	Universite Grenoble Alpes
10	36	India	10	6	Chinese Academy of Sciences

Note: The data has been taken from the publication year to retrieved date (December 20, 2025).

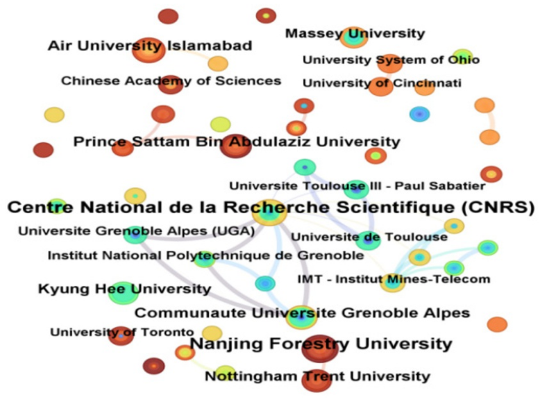

Fig. 3. Institutions involved in age-friendly smart home research worldwide (2006–2025).

3.3 Analysis of Journals and Cocited Journals

"Core journals" are significant publications characterized by elevated publishing and co-citation frequencies. Knowledge maps can offer insights into professional journals within a discipline.Table 4 delineates the fundamental publication landscape of age-friendly smart home research from 2006 to 2025. The field is dominated by engineering and technology journals, with Sensors (73 publications) and IEEE titles being the primary outlets. The presence of high-impact Q1 journals like IEEE Internet of Things Journal (IF: 8.9) and IEEE Journal of Biomedical and Health Informatics (IF: 6.8) signifies the convergence of cutting-edge IoT and healthcare informatics. Meanwhile, journals like International Journal of Environmental Research and Public Health reflect the important health and environmental dimensions. This portfolio demonstrates a highly interdisciplinary field where technological innovation is rigorously applied to health and well being in aging populations.

Table 4. Top 10 journals in age-friendly smart home research (2006 - 2025).

Ranking	Publications	Journal	IF (Q)
1	73	Sensors	3.5(Q2)
2	29	IEEE Access	3.6(Q2)
3	15	Applied Sciences-Basel	2.5(Q3)
4	14	IEEE Sensors Journal	4.5(Q2)
5	13	IEEE Internet of Things Journal	8.9(Q1)
6	13	International Journal of Environmental Research and Public Health	4.614(Q2)
7	10	Electronics	2.6(Q3)
8	10	Journal of Ambient Intelligence and Humanized Computing	N/A (ESCI Only)
9	9	Indoor and Built Environment	2.9(Q3)
10	8	IEEE Journal of Biomedical and Health Informatics	6.8(Q1)

Note: IF(Impact factor) and Quartile based on Journal Citation Reports (JCR) 2024 release (June 2025). Journal of Ambient Intelligence and Humanized Computing is indexed in ESCI but not (yet) in SCIE, thus has no JIF.

Generating a journal co-citation map using CiteSpace produced 360 nodes and 1,305 links, indicating a relatively mature and interconnected knowledge structure in age-friendly smart home research (Figure 4). As shown in Table 5 journals such as Sensors, Lecture Notes in Computer Science, and IEEE Access show the highest co-citation frequencies, reflecting their foundational role in sensor technologies, computing methods, and smart systems. Meanwhile, journals with high betweenness centrality, including Technology and Health Care, Medical Informatics and the Internet in Medicine, and the Journal of Telemedicine and Telecare, function as key interdisciplinary bridges linking engineering, informatics, and healthcare domains, highlighting the field's strong technological–medical integration.

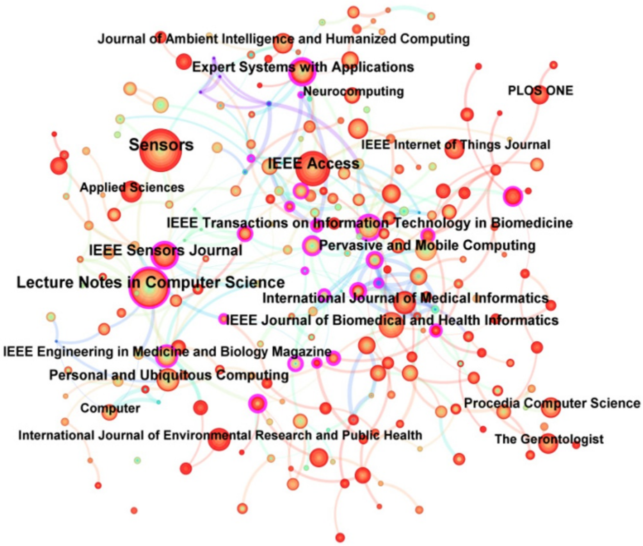

Fig. 4. Journal co-citation network in age-friendly smart home research (2006–2025).

Table 5. Top 10 co-cited journals and their centrality in age-friendly smart home research.

Ranking	Citation Count	Cited Journals	Ranking	Centrality	Journal Title
1	346	Sensors	1	0.54	Technology and Health Care
2	298	Lecture Notes in Computer Science	2	0.49	Medical Informatics and the Internet in Medicine
3	220	IEEE Access	3	0.4	Journal of Telemedicine and Telecare
4	150	IEEE Sensors Journal	4	0.36	IEEE Transactions on Information Technology in Biomedicine
5	142	IEEE Journal of Biomedical and Health Informatics	5	0.34	Computer Methods and Programs in Biomedicine
6	140	International Journal of Medical Informatics	6	0.31	Energy Policy
7	138	Expert Systems with Applications	7	0.29	IEEE Sensors Journal

Ranking	Citation Count	Cited Journals	Rank-ing	Cen-trality	Journal Title
8	133	IEEE Transactions on Information Technology in Biomedicine	8	0.29	IEEE Pervasive Computing
9	124	Pervasive and Mobile Computing	9	0.25	Studies in Health Technology and Informatics
10	123	Personal and Ubiquitous Computing	10	0.22	MIS Quarterly

Note:The data has been taken from the publication year to retrieved date (December 20, 2025).

3.4 Analysis of Author and Cocited Author

Knowledge maps are effective tools for identifying influential research groups and potential collaborators, thereby facilitating academic cooperation. The co-author network generated by CiteSpace consists of 381 nodes and 527 links, representing 381 authors who contributed to 700 publications in the field of age-friendly smart homes (Figure 5). The relatively sparse network structure suggests that collaboration among researchers is still developing and has not yet formed large, stable research clusters. As shown in Table 6 Kaner, Jake and Zhou, Chengmin are the most productive authors, each with eight publications, followed by Huang, Ting and Kim, Jeong Tai. These highly active authors constitute the core contributors to the field and are valuable targets for future collaboration and academic exchange.

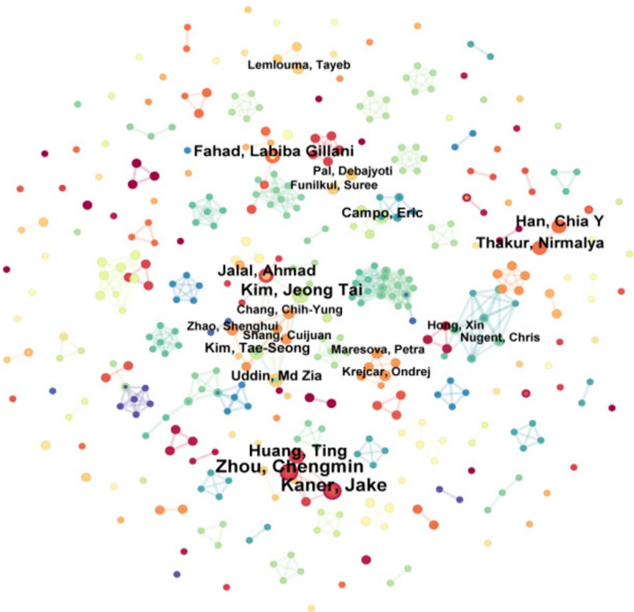

Fig. 5. Co-authorship network related to age-friendly smart home research (2006–2025).

Table 6. Top 10 active authors in age-friendly smart home research (2006 – 2025).

Ranking	Publications	Author	Ranking	Publications	Author
1	8	Kaner, Jake	6	5	Thakur, Nirmalya
2	8	Zhou, Chengmin	7	5	Han, Chia Y
3	6	Huang, Ting	8	5	Jalal, Ahmad
4	6	Kim, Jeong Tai	9	4	Uddin, Md Zia
5	5	Fahad, Labiba Gillani	10	4	Kim, Tae-Seong

Note:The data has been taken from the publication year to retrieved date (December 20, 2025).

Kaner, Jake focuses on age-friendly smart home interface design, using eye-tracking and physiological measurements to optimize elderly users' interaction performance, enhancing usability and emotional experience via evidence-based design improvements[24], [26], [28], [33], [34], [35], [36], [37], [38].

Zhou, C. focuses on age-friendly smart home interfaces for the elderly, using eye-tracking/EEG to optimize interaction performance and usability via evidence-based empirical research[24], [26], [35].

The author co-citation network comprises 429 nodes and 1,049 links, reflecting a relatively mature intellectual structure in age-friendly smart home research (Figure 6). As shown in Table 7, Cook DJ has the highest co-citation count, indicating her seminal contributions to smart environments and assisted living technologies. Chan M and Rashidi P also rank highly, highlighting their influence in sensor-based monitoring and intelligent healthcare systems. From the perspective of betweenness centrality, Chan M and Courtney KL occupy key bridging positions, suggesting that their work connects multiple research themes. Overall, these highly co-cited authors represent the core knowledge base and play a crucial role in shaping the theoretical and methodological development of the field.

Cook, DJ focuses on smart home-based functional health assessment for older adults: developing automatic activity recognition systems via unobtrusive sensor data to monitor behavior patterns and detect aging populations' functional decline[39].

Chan, M pioneers smart home technology for elderly care, conducting comprehensive reviews on sensor-based monitoring systems and assistive technologies to support independent living and healthcare applications[21], [23].

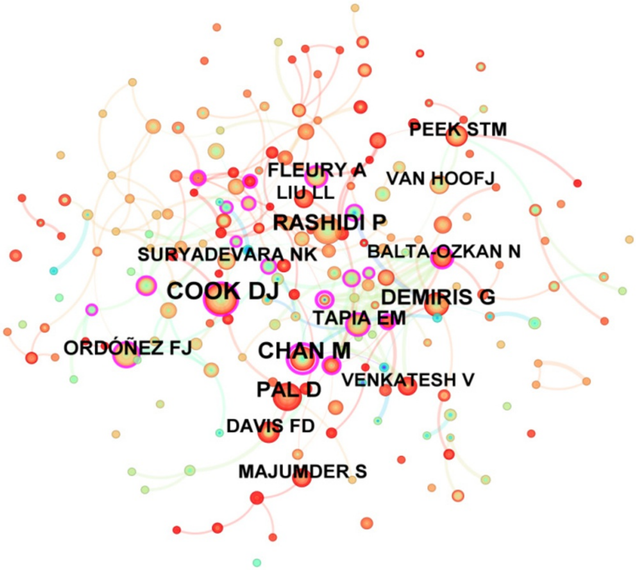

Fig. 6. Author co-citation network related to age-friendly smart home research (2006–2025).

Table 7. Top five co-cited authors in age-friendly smart home research based on co-citation counts and centrality.

Ranking	Cocitation Counts	Cited Author	Ranking	Centrality	Cited Author
1	107	COOK DJ	1	0.71	CHAN M
2	80	CHAN M	2	0.63	COURTNEY KL
3	72	RASHIDI P	3	0.21	COURTNEY KARENL
4	67	DEMIRIS G	4	0.19	TAPIA EM
5	61	PAL D	5	0.19	BALTA-OZKAN N

Note: The data has been taken from the publication year to retrieved date (December 20, 2025).

3.5 Analysis of Cocited References

A co-citation analysis of references yielded a network of 505 nodes and 987 links (Figure 7), indicating a well-developed and interconnected knowledge base in age-friendly smart home research. Analysis of co-citation frequency and betweenness centrality (Table 8,Table 9 and Figure 7) reveals that literature over the past two decades has primarily focused on four key areas:1) Technology Acceptance and User Behavior in Age-Friendly Smart Homes[40], [41], 2) Multimodal Sensing and Activity Recognition Technologies[42], [43],3) Health Monitoring and Assisted Living System Design[21], [44], 4) Ethical and Privacy Concerns in Technology Implementation [29], [45].

Highly co-cited references, such as Marikyan[46], Pal [47], and Majumder [48], form the core knowledge base, while high-centrality works by Deen [49], Alaa [50] and Nikou, S. [51] play key bridging roles linking technological, healthcare, and social research perspectives.

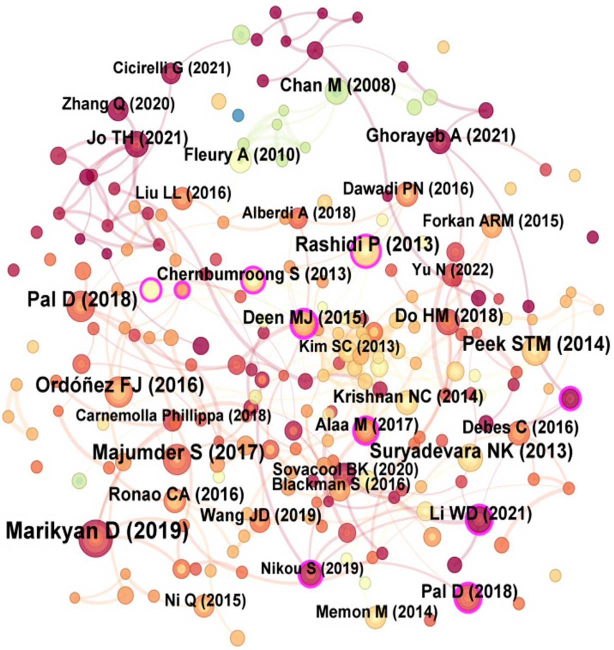

Fig. 7. Reference co-citation network related to age-friendly smart home research (2006–2025).

Table 8. Top five co-cited references in age-friendly smart home research based on co-citation counts.

Ranking	Cocitation Counts	Cited References	Representative Author (publication year)
1	23	Internet of Things for Smart Homes: A Review of Challenges and Opportunities	Marikyan (2019)
2	17	A Review of Smart Homes—Present State and Future Challenges	Pal (2018)
3	16	Smart Homes for Elderly Healthcare—Recent Advances and Research Challenges	Majumder (2017)
4	16	Activity Recognition Using Wearable Sensors for Ambient Assisted Living	Ordóñez (2016)
5	14	Factors Influencing Acceptance of Technology for Aging in Place	Peek (2014)

Note:The data has been taken from the publication year to retrieved date (December 20, 2025).

Table 9. Top five co-cited references in age-friendly smart home research based on centrality.

Ranking	Centrality	Cited References	Representative Author (publication year)
1	0.31	A survey of smart homes for aging in place	Deen, M. J. (2015)
2	0.17	A review of smart home applications for elderly care	Alaa, M. (2017)
3	0.16	Factors influencing the adoption of smart home technologies for older adults	Nikou, S. (2019)
4	0.13	Energy-related smart home technologies and social acceptance	Li, W. D. (2021)
5	0.13	User acceptance of smart home technologies: A systematic review	Pal, D. (2018)

Note: The data has been taken from the publication year to retrieved date (December 20, 2025).

3.6 Analysis of Keyword Cooccurrence and Burst Keywords

Over time, a knowledge map of keyword co-occurrence may reveal trending subjects, whereas burst keywords (those often referenced within a specific timeframe) may signify cutting-edge issues. Figure 8 and Table 10 illustrate the keyword co-occurrence structure of age-friendly smart home research from 2006 to 2025. The network comprises 226 nodes and 842 links, indicating a highly interconnected research field. The keyword "smart home" shows the highest frequency, confirming its central role. High-frequency terms such as "activity recognition," "older adults," "Internet of Things," and "ambient assisted living" reflect the strong technological orientation of the field. In contrast, keywords with high centrality, including "care," "framework," "elderly people," and "ambient intelligence," act as bridges linking technological development with care-oriented applications. The presence of "acceptance," "activities of daily living," and "dementia" highlights an increasing emphasis on user-centered design and real-world applicability, suggesting a shift toward more human-centric and health-focused smart home research.

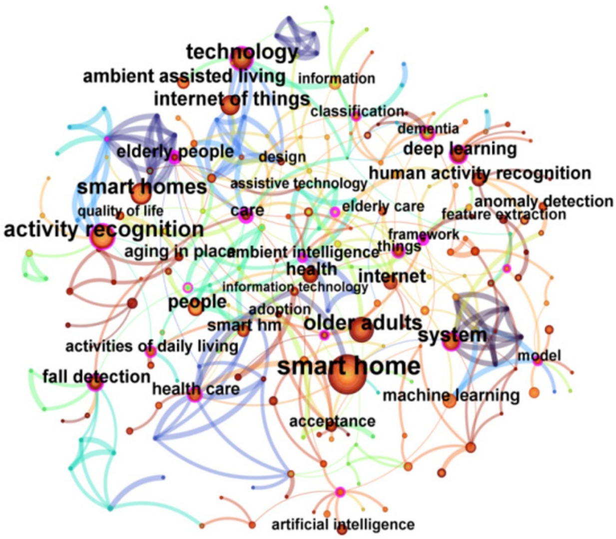

Fig. 8. Keyword co-occurrence analysis and visualization of age-friendly smart home research (2006 – 2025).

Table 10. Top 20 keywords in terms of frequency and centrality in age-friendly smart homes research.

Ranking	Frequency	Keyword	Ranking	Centrality	Keyword
1	233	smart home	1	0.26	care
2	94	activity recognition	2	0.26	framework
3	87	smart homes	3	0.22	elderly people
4	79	technology	4	0.22	ambient intelligence
5	75	older adults	5	0.21	fall detection system
6	72	system	6	0.18	things
7	50	internet of things	7	0.18	ambient assisted living (aal)
8	47	people	8	0.17	health care
9	44	internet	9	0.15	activity recognition
10	41	ambient assisted living	10	0.15	fall detection
11	40	deep learning	11	0.15	classification
12	39	human activity recognition	12	0.15	feature selection
13	37	elderly people	13	0.14	human-computer interaction
14	34	fall detection	14	0.13	dementia

15	34	health	15	0.12	model
16	33	health care	16	0.11	technology
17	32	care	17	0.11	system
18	32	smart hm	18	0.11	deep learning
19	29	machine learn-ing	19	0.11	activities of daily living
20	29	aging in place	20	0.1	acceptance

Note: The data has been taken from the publication year to retrieved date (December 20, 2025).

Figure 9 presents the keyword clustering map of age-friendly smart home research from 2006 to 2025. The keyword network consisted of 226 nodes and 391 links, with a density of 0.0154. A total of 12 major clusters were identified. The modularity Q value was 0.7166, indicating a clear modular structure, while the weighted mean silhouette score was 0.8922, suggesting high clustering reliability.

As shown in Table 11, the largest cluster was Cluster #0 "activities of daily living" (size = 29, silhouette = 0.842, mean year = 2016), followed by Cluster #1 "feature extraction" and Cluster #2 "older people." Earlier clusters, such as "smart homes," "ambient intelligence," and "smart care," reflect the foundational focus on smart environments, sensor networks, and assisted living. More recent clusters, including "internet of things," "human-computer interaction," and "digital health," indicate a shift toward connected healthcare, AI-enabled applications, privacy, security, and user-centered smart home systems.

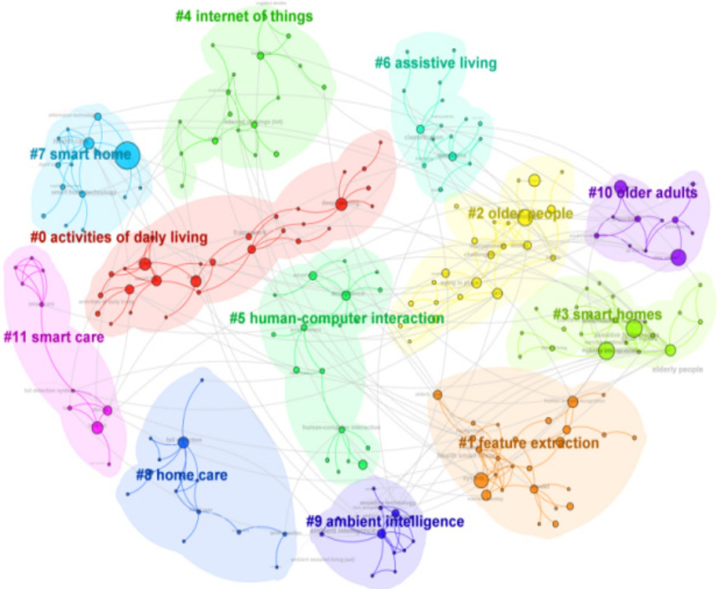

Fig. 9. Keyword clustering map of age-friendly smart home research (2006 – 2025).

Table 11. Major keyword clusters in age-friendly smart home research.

ID	label	Size	Silhouette	Mean year	Main interpretation
#0	Activities of daily living	29	0.842	2016	Daily activity monitoring, deep learning, human activity recognition, and anomaly detection
#1	Feature extraction	26	0.935	2014	Feature extraction, wearable sensors, real-time systems, and computational modelling
#2	Older people	23	0.957	2015	Quality of life, older adults, geriatric care, and independent living
#3	Smart homes	22	0.919	2012	Smart homes, activity recognition, context awareness, and activity prediction
#4	Internet of Things	18	0.788	2019	IoT, pervasive healthcare, energy-harvesting sensors, and daily activity recognition
#5	Human-computer interaction	18	0.909	2019	Human-computer interaction, digital health, AI, and activity recognition
#6	Assistive living	16	0.794	2016	Assistive living, activity monitoring, motor impairment, and brain-computer interfaces
#7	Smart home	15	0.981	2012	User behavior recognition, frailty, smart homes, and robotic things
#8	Home care	14	0.957	2015	Home care, active aging, machine vision, and detection technologies
#9	Ambient intelligence	12	0.903	2013	Ambient intelligence, assistive technology, spatio-temporal reasoning, and passive localization
#10	Internet of Things	11	0.791	2017	IoT, older adults, diseases, privacy, and security
#11	Smart care	10	0.909	2012	Smart care, aged people, few-shot learning, intelligent agents, and perception modelling

Note: Cluster labels were generated using the LLR algorithm in CiteSpace. Size refers to the number of keywords in each cluster, silhouette indicates cluster consistency, and mean year represents the average publication year of keywords within the cluster.

Burst words" refer to terms that are mentioned with high frequency over a specific duration. CiteSpace was employed to identify burst keywords, regarded as markers of emerging research frontiers throughout time. Figure 10 illustrates three frontiers in the research of age-friendly smart homes:

Technological Evolution: The shift from foundational concepts like ambient intelligence and smart homes towards advanced machine learning and deep learning algorithms for activity recognition and system intelligence[29], [42], [43].

Focus on the User: The progression from general terms like people and assisted living to more specific, person-centered terminology such as older adults, senior citizens, and older people, highlighting a refined focus on the target demographic[21], [40], [41].

Application & Impact: The sustained research interest in enabling physical activity and supporting activities of daily living within smart home environments, directly linking technology to health and wellness outcomes for the elderly[22], [41], [48].

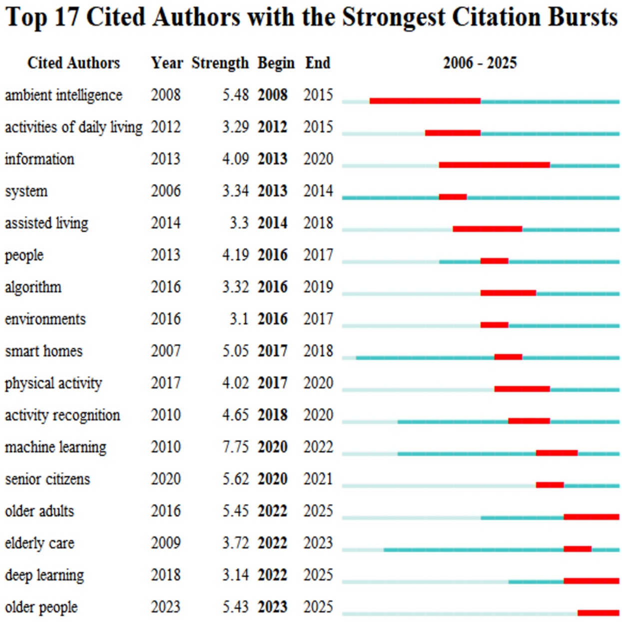

Fig. 10. Top 17 keywords with the strongest citation bursts in age-friendly smart home research (2006–2025).

4 Discussion

This section delves into the bibliometric results (cluster analysis and burst term evolution) to explore the trajectory of age-friendly smart home technologies in networking, artificial intelligence, and user privacy, while elucidating how these technological breakthroughs tangibly advance the United Nations Sustainable Development Goals (SDGs).

4.1 Integrating Technical Evolution with SDGs Progress

The bibliometric data indicates a paradigm shift in age-friendly smart home research from "basic environmental monitoring" to "predictive health management," providing crucial technical support for achieving SDG 3 (Good Health and Well-being) and SDG 11 (Sustainable Cities and Communities). Traditional passive call systems can no longer meet the growing demands of aging populations. Current research has advanced to utilizing sophisticated algorithms to predict latent health risks among the elderly. For instance, genetic algorithms are employed to extract cyclical patterns of daily activities, thereby offering early interventions for patients with mild cognitive impairment (MCI) or dementia[52]. Furthermore, Internet of Things (IoT) architectures are not limited to fall detection but are innovatively applied to monitor the "social isolation" status of elderly individuals living alone [53], as well as indoor air pollutant concentrations (e.g., via low-cost embedded HOPES systems) [54]. These multi-dimensional intelligent sensing technologies are gradually transforming traditional residences into sustainable smart nodes equipped with comprehensive health care capabilities.

4.2 Paradigm Shift in Networking: From Ambient Sensors to Seamless IoT

As illustrated by the burst term mapping, "Internet of Things" is the most prominent keyword over the past decade (with a burst strength of 6.74). This signifies a qualitative leap in the underlying network architecture of age-friendly smart homes: evolving from early, isolated Ambient Assisted Living (AAL) systems to highly interconnected, multi-modal modern IoT architectures. To address elderly users' reluctance towards wearable devices, current sensor networks are trending towards "non-intrusive" and "non-tagged" directions. For example, recent studies propose multimodal indoor localization architectures combining pyroelectric infrared (PIR) sensors and smart floor pressure, achieving accurate tracking without requiring the elderly to wear any intrusive devices [55]. Meanwhile, to reduce network latency and protect edge data privacy, edge computing gateways based on lightweight open-source software frameworks (such as the MUS3E framework) have been introduced into age-friendly environments. This enables physiological data computation and risk assessment to be performed locally at the home gateway, significantly enhancing the real-time responsiveness and deployment economy of IoT systems [56].

4.3 AI-Driven Smart Care: Deep Learning and Activity Recognition

With “machine learning,” “deep learning,” and “activity recognition” emerging as prominent burst terms after 2020, the role of computational intelligence in age-friendly smart homes has become increasingly practical. Rather than being limited to general pattern classification, these methods are now closely associated with fall detection, daily activity recognition, functional health assessment, and adaptive home-care services.

First, machine learning and deep learning have been widely used for fall detection and abnormal-event recognition. For example, hybrid models combining 1D Convolutional Neural Networks (1D CNN) and Long Short-Term Memory (LSTM) networks have been applied to point-cloud kinematic features generated by FMCW millimeter-wave radar, enabling real-time fall detection with high accuracy and low latency [57]. In vision-based monitoring, models integrating YOLOv8 object detection with time-space transformers have been used to improve the extraction of temporal motion features and reduce false alarms in complex home environments [58].

Second, these methods support human activity recognition and functional health assessment. By analyzing data from wearable sensors, radar, visual devices, and ambient sensors, smart home systems can identify activities of daily living and detect deviations from regular behavioral routines. Such functions are important for recognizing potential frailty, cognitive decline, or abnormal behavior among older adults. For users with different levels of physical ability, Deep Belief Networks combined with optimization algorithms have also been introduced into human activity recognition tasks to improve model adaptability and generalizations[59].

Third, intelligent algorithms contribute to more adaptive and personalized homecare services. By learning individual behavior patterns, smart home systems can support environmental adjustment, medication reminders, emergency alerts, and caregiver notifications. These functions are particularly relevant to aging-in-place scenarios, where older adults require continuous support while maintaining independence and privacy.

Finally, recent studies increasingly emphasize non-intrusive and privacy-preserving sensing. Technologies such as millimeter-wave radar, thermal imaging, and non-wearable sensor fusion can support activity recognition and safety monitoring without continuously collecting identifiable visual information. Therefore, the citation bursts of machine learning and deep learning indicate not only methodological development, but also a broader transition from passive ambient monitoring toward predictive, adaptive, and privacy-aware smart care systems.

4.4 User Acceptance, Privacy Challenges, and Future Directions

Despite the rapid development of AI and networking technologies, the explosion of the term "privacy" (2022-2025) in the burst mapping indicates that technological implementation faces severe social and ethical challenges. Empirical studies utilizing the Technology Acceptance Model (TAM) point out that the fear of "being monitored" and the "digital divide" are the greatest barriers hindering the adoption of smart homes among the elderly[60]. To resolve this "privacy paradox," future research trends are comprehensively shifting towards privacy-preserving sensing. In addition to the aforementioned millimeter-wave radar technology, thermal imaging sensors are widely utilized in lightweight smart home gesture recognition and interactive control because they can operate in low light and completely eradicate facial identity features[61]. Furthermore, radio frequency signal analysis based on Commercial Off-The-Shelf (COTS) RFID devices (such as the RF-PSignal system) achieves contactless interaction across wide areas through the extraction of signal phase and strength topological features[62]. Concurrently, to bridge the digital divide caused by complex smartphone applications, academia has even explored IoT remote control solutions based on traditional telephone Dual Tone Multi-Frequency (DTMF) signaling[63]. In the future, striking a balance between complex upper-layer deep learning algorithms and underlying privacy-preserving hardware will be a critical direction for researchers in the AINIT domain to continuously explore.

5 Limitations

Although this study provides a systematic bibliometric overview of age-friendly smart home research, several limitations should be acknowledged. First, the bibliographic data were retrieved only from the Web of Science Core Collection. Although WoS provides high-quality citation metadata and is widely used in bibliometric research, reliance on a single database may have excluded some relevant studies indexed in other databases. In particular, IEEE Xplore may contain additional applied engineering and technical conference papers on smart home systems, sensors, IoT architectures, embedded devices, and assistive technologies; PubMed may provide more clinically oriented studies related to elderly healthcare, chronic disease management, rehabilitation, nursing care, and gerontechnology applications; and Scopus may offer broader coverage of interdisciplinary publications and conference proceedings. Therefore, the current dataset may not fully capture all engineering-oriented and clinical perspectives in this field.

Future studies should consider integrating multiple databases, such as WoS, Scopus, IEEE Xplore, and PubMed, to construct a more comprehensive dataset. Cross-database comparison, deduplication, and sensitivity analysis could help identify differences in disciplinary coverage, citation patterns, collaboration networks, and thematic evolution. Such an approach would further improve the comprehensiveness and robustness of bibliometric mapping in age-friendly smart home research.

6 Conclusion

From the current bibliometric analysis of age-friendly smart homes publications over the previous 20 years (2006–2025), it was found that related publications showed a steady growth trajectory, entering a stable and mature phase with sustained academic attention after rapid expansion post-2018. China, the United Kingdom, and the United States, with high publication volumes, were demonstrated to be the main research powers in this field, reflecting a diversified yet regionally concentrated global landscape. The Centre National de la Recherche Scientifique, Nanjing Forestry University, and Communaute Universite Grenoble Alpes were leading institutions, each with distinct research focuses from sensor technologies to user-centered design.

The field is highly interdisciplinary, with core journals spanning engineering (e.g., Sensors, IEEE Access) and healthcare (e.g., IEEE Journal of Biomedical and Health Informatics), indicating convergence of IoT and health informatics. Kaner, Jake and Zhou, Chengmin were the most productive authors, while Cook, D.J. had the highest citation impact, highlighting key contributors to interface design and smart environment technologies.

Keyword analysis revealed central themes of "smart home," "activity recognition," and "older adults," with burst keywords like machine learning, deep learning, and elderly care indicating shifts toward advanced AI and user-centered applications. Research frontiers included technological evolution (from ambient intelligence to AI algorithms), user focus (refined terminology for older adults), and application impact (linking technology to daily living support).

In conclusion, this study provides insights into the global landscape of age-friendly smart home research, identifying major contributors, interdisciplinary trends, and emerging frontiers. It offers valuable information for researchers to identify collaborators, key topics, and future directions, emphasizing the need for enhanced international collaboration to advance practice.

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