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Original Research

AI empowered nursing of cognitive impairment: research status, hotspot analysis, and future trends

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Abstract: Background: AI assists in cognitive impairment care by enabling data-driven approaches to reduce burden and increase efficiency. **Methods:** This system evaluation is based on the WOS core collection (retrieved as of June 13, 2025), using bibliometric methods to analyze the current status, hotspots, and trends of AI in the diagnosis and treatment of cognitive impairment from multiple dimensions such as publications, authors, funding, and patents. It also delves into high impact literature and reveals the potential synergistic effects of the two studies. **Results:** In this study, 7,285 articles from 200 journals and 119 countries were analyzed. Funding is mainly provided by the National Institutes of Health in the United States, followed by the National Natural Science Foundation of China and multinational corporations. The number of patents on artificial intelligence continues to grow, focusing on four major areas: medical imaging, new drug development, personalized treatment, and risk prediction, highlighting their critical role in addressing complex medical challenges. **Conclusion:** Research in the field of AI for cognitive impairment is developing rapidly, focusing on multi-source data and radiomics, but still faces challenges such as algorithm transfer, clinical validation, and interdisciplinary collaboration. In the future, it is necessary to strengthen international cooperation, promote the integration of explainable AI and real data, and improve the accuracy of diagnosis and treatment.

Keywords: Artificial intelligence, Cognitive impairment, Bibliometric analysis

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1. Introduction

As one of the core clinical manifestations of mental disorders [1], cognitive dysfunction affects multiple cognitive domains, including attention maintenance, information processing efficiency, working memory capacity, verbal memory encoding and retrieval, executive control, and social cognition [2]. Epidemiological studies indicate that even in individuals who do not meet the diagnostic criteria for schizophrenia, the cognitive performance of most patients remains significantly below population norms [1]. With the accelerating global aging population, the prevalence of cognitive impairment continues to rise. Projections suggest that the population of global patients will exceed 152 million by 2050 [3]. Furthermore, the 2021 Global Burden of Disease Study confirmed that Alzheimer's disease (AD) and related dementias have risen to the eighth leading cause of death worldwide [4]. Epidemiological data from the US indicates that there were 5.8 million AD cases in 2020, and estimates suggest that the number will almost triple to 14 million by 2050. The rapid increase in AD prevalence not only impairs patients' physical health, cognitive function, and psychosocial adaptability, but also significantly diminishes their ability to live independently, posing severe challenges to current care systems [5] In particular, no effective treatments currently exist to slow or reverse the pathological progression of the disease.

The AD diagnosis and treatment system faces a dual dilemma: on the one hand, the disease develops progressively, with early symptoms being subtle and non-specific, leading to clinical diagnoses often occurring at irreversible pathological stages. On the other hand, existing non-pharmacological interventions (e.g., music therapy, exercise training, and cognitive rehabilitation [6]) can partially alleviate symptoms, but are generally limited by modest effect sizes and suboptimal cost-effectiveness [7]. In this context, applications of assistive technology (AT) in cognitive impairment interventions have become increasingly widespread, as manifested in:

(1) the enhanced clinical translation of virtual reality/augmented reality technologies;
(2) the development of adaptive algorithm-based cognitive training systems for tablets;
(3) advancements in smart home environmental sensing technologies.

In 2016, the US National Science and Technology Council established a dedicated task force aimed at improving independent living capabilities in elderly patients with cognitive impairment through technological innovation. A 2019 policy report explicitly highlighted the strategic value of emerging technologies such as artificial intelligence (AI) in optimizing patient quality of life, maintaining autonomous functions, and reducing care costs [8].

As an interdisciplinary field integrating computer and data science, AI fundamentally seeks to simulate and extend human cognitive functions through machine learning algorithms. Technically defined, AI systems can extract feature patterns from massive training datasets and generalize these inferences to new data [9]. Machine learning (ML) and deep learning (DL) as core AI frameworks demonstrate significant advantages in multimodal medical data analysis. The clinical application of these technologies is driving the transformation of cognitive impairment diagnostics and treatment toward precision and personalization. Notably, AI-powered smart care technologies not only enhance the efficacy of traditional care, but also achieve synergistic improvements in patient autonomy and social participation through home-environment adaptation technologies [10].

2. Research problem and aim

In this study, bibliometric methods were used to systematically investigate the application trends and development trajectories of artificial intelligence in the field of cognitive impairment nursing. Considering that the current application of artificial intelligence technology in the field of cognitive impairment is still in the exploratory stage, and the number of publications is relatively limited, we focus our research on the following three dimensions: Firstly, we conducted a temporal analysis of the literature published between 2015 and 2025 to explore the characteristics and early development trajectory of artificial intelligence technology extending from the general field to the field of cognitive impairment. Secondly, in the early stages of AI-assisted nursing for patients with cognitive impairment, we determined the geographical distribution by analyzing the geographic information of authors and institutions, major research centers, and active countries. Finally, we conducted a thorough analysis of funding situation, particularly in the early stages of technology, as well as funding support from governments and multinational research organizations.

3. Methods

In this study, a writing method combining bibliometrics and scope review was applied. Based on a search in the Web of Science core database, 5,615 selected literatures were used to conduct a multidimensional empirical research on the application of artificial intelligence in the field of cognitive impairment. Through systematic quantitative analysis methods, this study not only reveals the research patterns, knowledge structures, and cutting-edge hotspots in this field, but also provides scientific predictions about possible future research directions. This study strictly followed the PRISMA framework for literature screening and utilized professional tools such as VOSviewer and Citespace to achieve data visualization, clearly presenting the entire process of bibliometric analysis and scope review. This mixed methods research design provides evidence-based support for intelligent interventions for cognitive impairment, and also indicates a research path with practical value in this field.

3.1 Data sources and search strategy

This study strictly followed the bibliometric research standards proposed by Donthu et al. [11]. In order to avoid potential bias in the data during the process of converting multiple databases, the research team adopted a single database source strategy. After a systematic evaluation, we ultimately chose Web of Science Core Collection (WoS CC) as the source for literature data collection for the following reasons: firstly, the platform integrates all sub-databases of the citation index, which can maximize the completeness of the included literature; secondly, as an internationally recognized authoritative academic resource, the data quality of WoS-CC has been fully validated in multiple methodological studies [12].

During the data collection phase, the research team implemented strict quality control measures: all members received systematic training based on the standard textbook "Medical Literature Retrieval" [13] and conducted a unified retrieval operation on June 13, 2025. The search strategy used the keyword expansion method to construct Boolean logical expressions containing core terms such as "artificial intelligence" and "cognitive impairment", as well as their derived terms and synonyms (Multimedia Appendix 1), with a time span from the database to the day of retrieval. After obtaining 7,285 literature records through a preliminary search, we exported the complete bibliographic data and citation network, and archived them in a standardized text format. It is worth noting that in order to eliminate the time deviation caused by the daily database updates, all retrieval and export operations were completed within 24 hours.

3.2 Inclusion and exclusion criteria for literature

The inclusion criteria are as follows: (1) The literature type is limited to peer-reviewed journal articles (designated as 'article' in WoS) or reviews; (2) Written in English; (3) The research topic is related to "artificial intelligence", "nursing", and "cognitive impairment".

The exclusion criteria are as follows: (1) duplicate publications; (2) literature that has not been published in journals, such as conference papers, books, and reviews; (3) literature with missing abstracts, keywords, or main text; (4) traditional nursing research that does not involve artificial intelligence technology; (5) research involves only general technology without the application of artificial intelligence technology; (6) research that does not target patients with cognitive impairment.

3.3 Screening strategy

After establishing inclusion and exclusion criteria, in order to ensure the reliability of the material selection, two evaluators (XL and YY) conducted a preliminary screening experiments on 50 papers based on titles, abstracts, and keywords [14]. The calculated value of the Cohen's kappa coefficient is about 0.88, indicating a high level of consistency among evaluators (the Cohen's kappa coefficient ranges from -1 to 1, with higher values indicating better consistency [15]); Specific formulas and methods can be found in Multimedia Appendix 2.

Therefore, we decided not to make any changes to the selection and exclusion criteria or evaluators. If there is any disagreement during the formal selection process, the three authors (SY, XL, and YY) will discuss the issue until a consensus is reached in the team meeting. Literature screening and verification was successfully completed on June 25, 2025. Out of the identified 7,285 papers, 5,615 (77.08%) were included and 1,670 (22.92%) were excluded. The detailed search and selection process is shown in Figure 1.

3.4 Data cleaning

In the data cleaning stage, a strict quality control process was implemented in this study to ensure data accuracy. In the process of author identification, the research team established a multidimensional verification mechanism: by cross referencing ORCID academic archives, publication histories, institutional affiliations, and information from academic social platforms (such as ResearchGate), accurate merging and integration of author records with similar or potentially duplicate names were carried out. This study used the standardization framework for institutional affiliations developed by Nam et al.[16] to process institutional data. For authors with multiple institutional affiliations, we prioritized identifying their primary affiliation institution as the main research unit and systematically standardized the full name and abbreviation of the institution to improve the accuracy of institutional analysis.

In addition, this study also pays particular attention to the academic connections between the author and international institutions, which are often reflected in cross-border visiting scholar projects or other forms of international cooperation, adding an international perspective to the analysis. In terms of research funding analysis, this study systematically sorted out all names of funding party, uniformly processing their full names and abbreviations to ensure the reliability of funding source analysis. Before conducting keyword analysis, in order to improve the consistency and accuracy of the analysis, we used the Bibliometrix software package in the R language to intelligently merge synonyms. For example, we merged "Alzheimer disease" and "AD" under "Alzheimer's disease". The detailed list of merged keywords can be

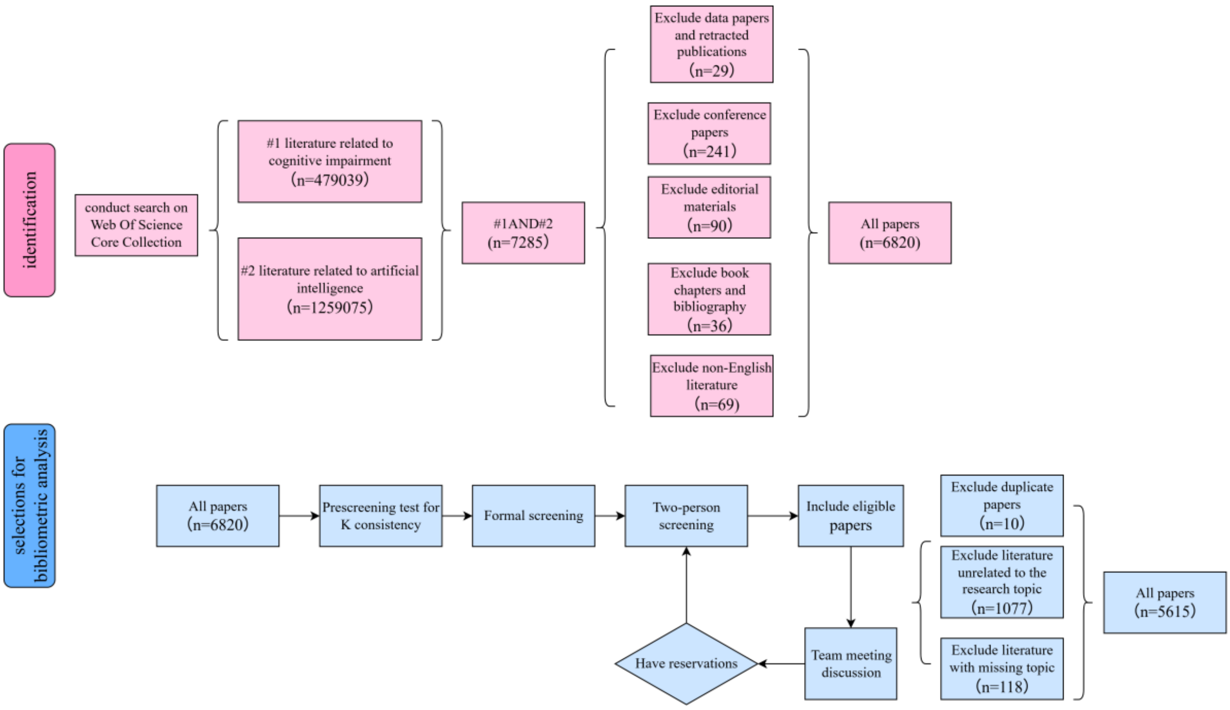


Figure 1. Flowchat of literature selection.

found in Multimedia Appendix 3 to ensure the rigor and depth of the analysis.

4. Results

4.1 The annual trends of publications

By analysing the literature published in the past 25 years (as shown in Figure 2), this study discovered the dynamic evolution characteristics of artificial intelligence technology in assisting cognitive impairment care. According to data analysis, we can see a clear three-stage transition pattern in the development of this field: from 2000 to 2008, it was the stage of technological germination (with an average annual output of 200-300 articles), from 2008 to 2016, it gradually entered a stable development period (with an average annual output of 300-450 articles), and after 2016, it showed an accelerated growth trend (with an average annual output of 450-600 articles). This growth trend is closely related to macro factors such as breakthroughs in deep learning technology, the accelerated global aging process, and surging demand for digital health.

And the overall research focus has also undergone significant changes. Early research mainly focused on the development of basic algorithms, while in recent years, the research focus has clearly shifted towards application directions such as the fusion analysis of multimodal data, the optimization of personalized care plans, and the integration of intelligent environmental systems. Based on the current development trends in this field, we believe that in the future, more attention can be paid to the clinical translation applications of generative AI technology, the challenges of technology adaptation in real-world scenarios, and the establishment of interdisciplinary collaborative innovation mechanisms to promote innovative development in this field.

4.2 Institutional analysis

The analysis of institutional outputs and collaboration models provides key insights into AI-assisted nursing research for patients with cognitive impairments. Through the analysis of Figure 3A, we can recognize that relevant research institutions have formed a dense collaborative network centered around the top academic institutions, and exhibited a clear structural distribution with a "core edge". This distribution characteristic also reveals the dual functions of research universities as hubs for knowledge innovation and platforms for collaborative research in this field.

By analysing the distribution of institution types (Figure 3B), we found that academic institutions currently occupy an absolutely dominant position. The statistical data shows that university institutions (76.3%, 142) contributed 61.6% of the literature output (864 articles), which also confirms their position as the main force of basic research. The participation rate of medical institutions (8.1%, 15 institutions) is in sharp contrast to their output proportion of 19.1% (268 articles), reflecting the particular value demonstrated by clinical institutions in application transformation. In addition, research institutions and government departments (9.7%, 18 institutions) and corporate entities (5.9%, 11 institutions) contributed 12.4% and 6.9% of research results, respectively, reflecting the pattern of collaborative innovation among multiple subjects in industry university research.

As for individual institutions, the University of London is the largest publisher, publishing 39 papers (1.23%). In Table1, we can also see that the research influence of the University of Cambridge is particularly prominent, with 3,108 citations (accounting for 20.09%) and 91.41 citations per article, demonstrating its academic leadership position. It is worth noting that institutions affiliated with the United States account for more than half of the top ten global publications, and this regional cluster phenomenon may stem from its well-established technology research and development system, abundant scientific research investment, and the mature cross- institutional cooperation mechanisms.

As the main body of research institutions, universities, hospitals, research institutions, and companies have made valuable contributions to this field. Therefore, identifying high-yield institutions and understanding their collaborative networks is crucial for better promoting research partnerships and further advancing research on artificial intelligence technology in the field of nursing care for patients with cognitive impairments in the future.

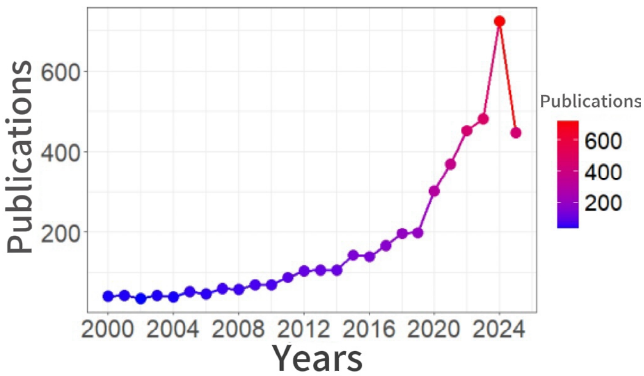


Figure 2. Trend analysis of annual publication volume of nursing care for patients with cognitive impairment assisted by artificial intelligence technology

4.3 Country analysis

Analyzing national output and cooperation models can provide a macro-level understanding of the application of artificial intelligence (AI) technology in the care of patients with cognitive impairments and identify research gaps and new trends in cooperation between countries. According to the research data, research institutions from 118 countries participated in the field, with the top 10 high-yielding countries contributing 5,482 results (accounting for 65.7% of the total output). These countries show a balanced geographical distribution: Europe, Asia, and the Americas each include three countries, while only one country comes from Oceania. In terms of literature output, citation frequency, breadth of international cooperation, and number of research institutions, the United States has advantages, which fully demonstrates its leadership position in this field. It is worth noting that we found that the GDP of all high-yielding countries ranks among the top 15 in the world, which also suggests a significant positive correlation between a country's economic strength and its research capacity (Table 2).

Through a visual analysis of the international cooperation network (Figure 4A), we found that node features well reflect the intensity and output scale of scientific research cooperation at the national level. China, the United States, Germany and other countries form the central system of the research network through intensive cooperative connections, and have now formed core hub nodes. Regional analysis shows that European countries exhibit a highly concentrated network of cooperation, while research collaboration between Asian countries currently is relatively limited. In sharp contrast, some African and South American countries are located at the edge of the internet due to limited scientific research resources, and have less cooperation with neighboring countries, especially with those having strong scientific research capabilities. Therefore, on the basis of existing cooperationin, the cooperation with these marginalized countries should be strengthened in the future to better utilize global resources. The circular network diagram (Figure 4B) reveals the characteristics of international cooperation through further analysis. We found that

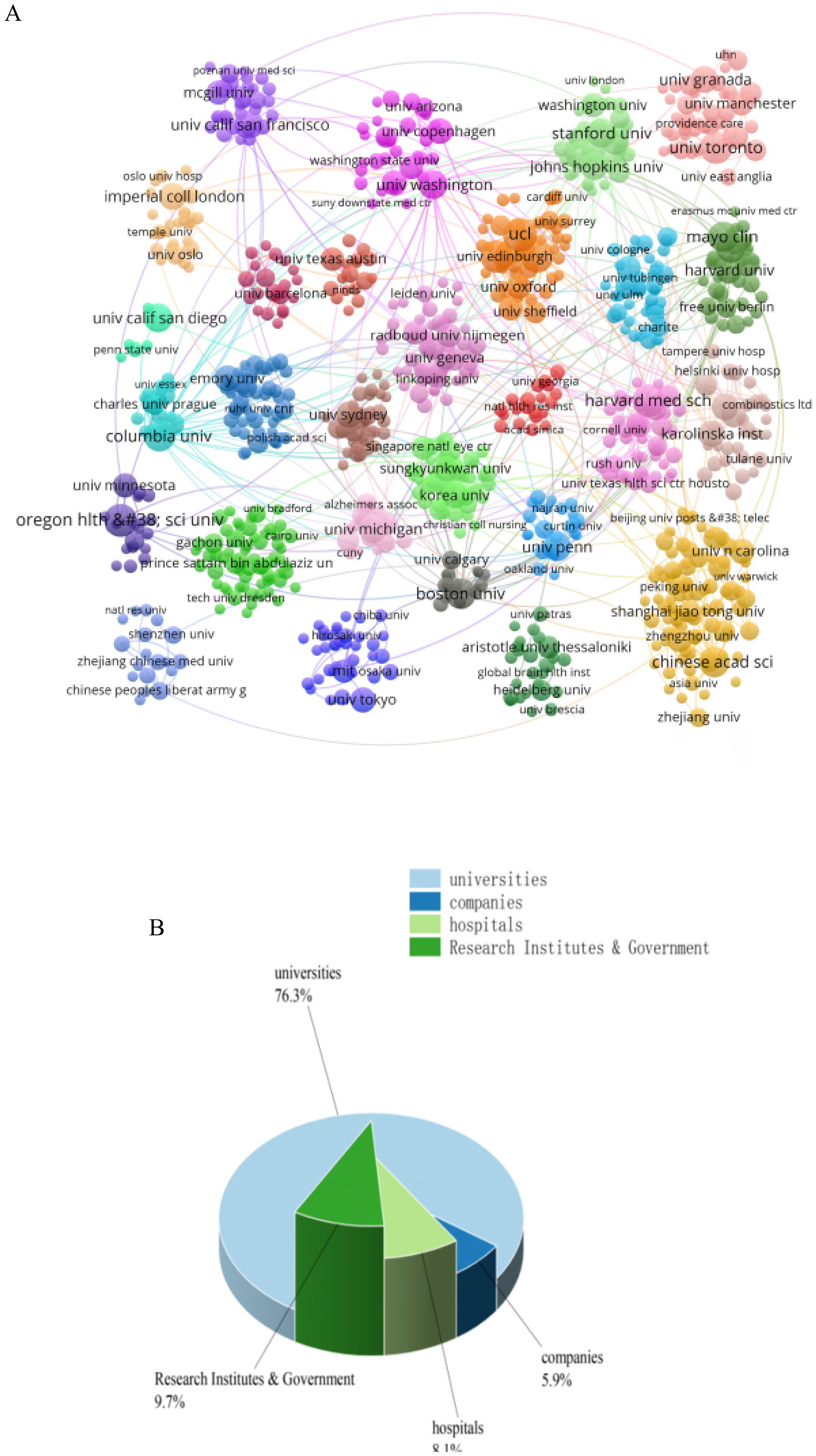


Figure 3. Institutional collaboration diagram of artificial intelligence technology participating in the care of patients with cognitive impairment. (A).The network diagram of institutional cooperation; (B). The type of institution involved in AI- assisted nursing care for patients with cognitive impairments.

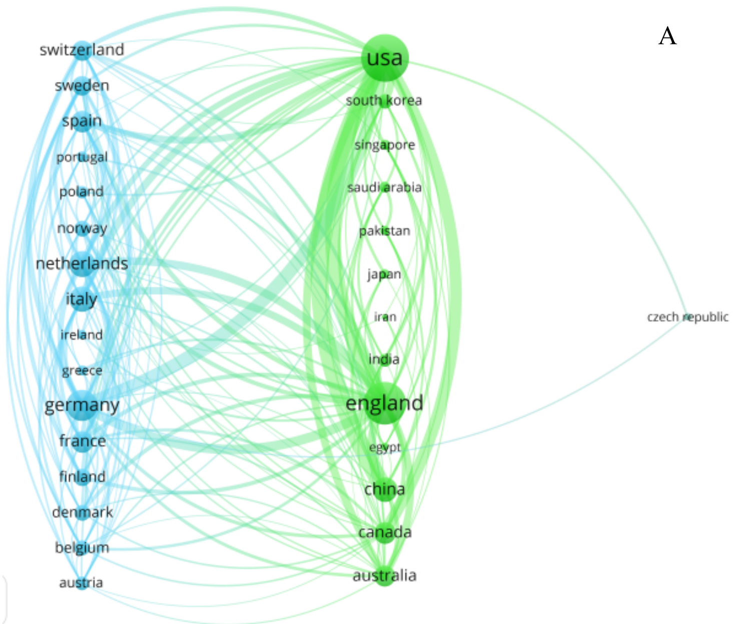
Notes: Color coding is used to represent the average time for constructing institutional collaboration networks.
The size of the circles increases with the number of publications.

countries such as the United States and Australia exhibit significant color scale differences based on cooperation intensity, and the density and direction of internal connection lines also intuitively reflect the depth and directionality of cross-border cooperation. In addition, we also found significant differences in research trajectories between countries. For example, as a pioneer in this field, the United States not only has the longest research history, but also has established research cooperation with more than 90 countries. The research cooperation between North America, led by the United States, and Europe is significantly closer than that between other regions and has long occupied a core position in the international cooperation network. European countries such as the UK and Germany have also demonstrated strong international cooperation capabilities and closely cooperate with other countries in the world. On the other hand, although China, Japan and other Asian countries have achieved significant scientific research output, the current cross-border cooperation is relatively limited. This also indicates that Asian countries need to further expand their international cooperation network in the future development process.

Table 1. Basic information of the top ten most productive institutions for nursing research on patients with cognitive impairment assisted by artificial intelligence technology

Rank	Organization	Output (N=341,n%)	Citations (N=154,74,n%)	aCPP	Country
1	University College London	39(11.4)	2,471(16.0)	63.4	United Kingdom
2	King's College London	38(11.1)	1,934(12.5)	50.9	United Kingdom
3	Oregon Health & Science University	38(11.1)	1,223(7.9)	32.2	United States
4	University of Toronto	35(10.3)	7,32(4.7)	21.0	Canada
5	Harvard Medical School	34(10.0)	1,033(6.7)	30.4	United States
6	University of Cambridge	34(10.0)	3,108(20.1)	91.4	United Kingdom
7	Columbia University	32(9.4)	817(5.3)	25.5	United States
8	Boston University	31(9.1)	1,212(7.8)	39.1	United States
9	Mayo Clinic	31(9.1)	1,883(12.2)	60.7	United States
10	Chinese Academy of Sciences	29(8.5)	1,061(6.9)	36.6	China

aCPP:citations per paper



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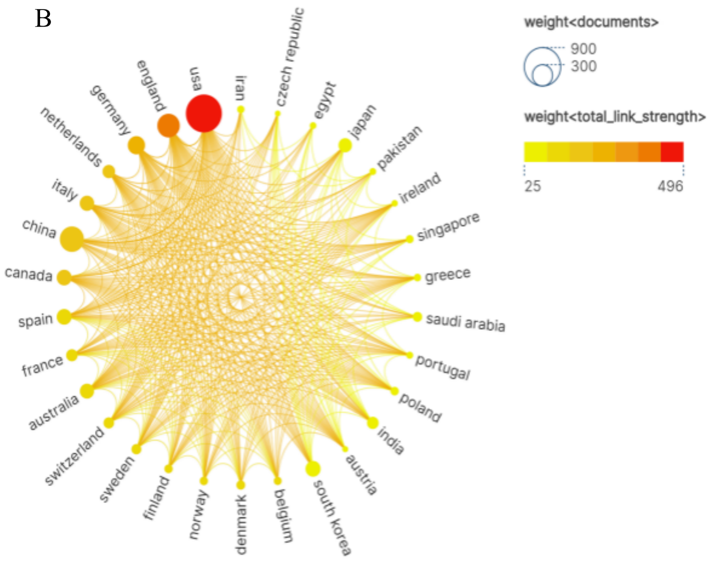


Figure 4. (A). Productivity of AI-assisted nursing research for cognitively impaired patients and cooperation between countries; (B). Diagram illustrating the collaborative institutional relationships among countries in related research fields for cognitively impaired patients.

Notes: These colors represent countries/regions and have no specific meaning;
Only the thickness of the lines between them is significant, indicating the frequency of cooperation between different countries. The thickness of the lines corresponds to the values on their respective axes.

Table 2. The top ten countries with the most effective research on AI assisted nursing for Alzheimer's disease patients: basic information

Rank	Country	Output (N=5,482,n%)	Citations (N=11,779,n%)	Organization (N=200,n%)	Partner countries (N=44,n%)	a2024GDP Rank	UN region
1	United States	1,759 (32.1)	3,296 (28.0)	58 (29.0)	28 (63.6)	1	Americas
2	China	793 (14.5)	481 (4.1)	14 (7.0)	4 (9.1)	2	Asia
3	United Kingdom	387 (7.1)	788 (6.7)	23 (11.5)	21 (47.7)	6	Europe
4	Germany	339 (6.2)	492 (4.2)	16 (8.0)	9 (20.5)	3	Americas
5	Canada	311 (5.7)	225 (1.9)	12 (6.0)	5 (11.4)	8	Americas
6	Italy	290 (5.3)	923 (7.8)	6 (3.0)	13 (29.6)	9	Europe
7	India	287 (5.2)	491 (4.2)	2 (1.0)	18 (40.9)	5	Asia
8	Australia	283 (5.2)	707 (6.0)	8 (4.0)	16 (36.4)	13	Oceania
9	Spain	253 (4.6)	399 (3.4)	6 (3.0)	10 (22.7)	14	Europe
10	Japan	235 (4.3)	308 (2.6)	3 (1.5)	11 (25.0)	4	Asia

4.4 Funding analysis

The analysis of funding sources has clearly revealed the distribution trends and characteristics of research funding. Through in-depth analysis of 200 funding entities, we found that the funding system in this field exhibits a clear hierarchical distribution. It is worth noting that the US government holds a significant advantage among the major funding agencies, with the Department of Health and Human Services (HHS) as the primary funder, receiving a large amount of funding support, providing a total of 871 research grants (accounting for 9.6%). The distribution of this data is detailed in Table 3.

According to the classification based on the nature of the funding subject (Figure 5), the current government financial allocation constitutes the main body of the entire research funding (41.6%), which highlights the fundamental supporting role played by the public sector in this field. The joint contribution by the business community and private capital of 26.5% of R&D funding also indicates that market forces play an important role in technological innovation and provide constructive assistance for research in this field. In addition, the funding from non-profit organizations (17.2%), academic institutions (9.8%), and international organizations (4.9%) together constitute a diversified funding source system, which has provided great assistance for research. Although the total proportion is relatively small, it precisely reflects the importance that various sectors of society attach to the use of artificial intelligence technology to assist in the care of patients with cognitive impairment, and the promising future of this hot topic in the research prospects.

4.5 Keyword analysis

Keyword analysis reveals the research trends, hot topics, and technological advancements in the field of artificial intelligence assisted nursing for patients with cognitive impairments. Before conducting a comprehensive analysis on the keywords, we implemented a strict data cleaning and ultimately extracted 261 keywords with a total occurrence of 7,777 times. According to the threshold set by Price's Law [17] (≥ 9 times), we identified a total of 118 high-frequency keywords (7,170 times in total, accounting for 91.19%), which collectively reflects the core research directions in this field.

The co-occurrence network analysis (Figure 6A) mainly identified four distinct thematic clusters:

(1) Red cluster: This cluster focuses on the application of deep learning technology in the diagnosis of neurodegenerative diseases (especially Alzheimer's disease), mainly involving clinical translational research such as biomarker recognition and development on tool for early screening;

(2) Green clusters: This cluster focuses on the epidemiological characteristics of patients with dementia, mainly covering risk factor assessment, prevention and intervention, and rehabilitation supporting technologies;

(3) Yellow cluster: This cluster mainly studies the phenotypic characteristics of cognitive behavioral disorders, including AI prediction models for dimensions such as memory deficits and executive dysfunction;

(4) Purple cluster: This cluster focuses on the standardized construction of disease classification systems and diagnostic and treatment norms, which better reflects the key role of research institutions in developing clinical guidelines.

From the analysis shown in Figure 6C, it can be seen that core terms such as "mild cognitive impairment" and "machine learning" continue to be research hotspots, which also reflect the dynamic integration process of new AI technologies and emerging clinical problems. With the continuous emergence and application of new technologies in clinical practice, the clinical problems that have plagued us in the past have been well solved, and it is also more helpful for alleviating patients' burden. The research has further confirmed (Figure 6B) that a multidisciplinary research pattern has been formed, for patients with dementia related diseases as research subjects and artificial intelligence technology, machine learning, and other advanced technologies as support. At the same time, the three pillars of standardized diagnosis, assessment of cognitive ability, and group intervention continue to prompt us for new research directions.

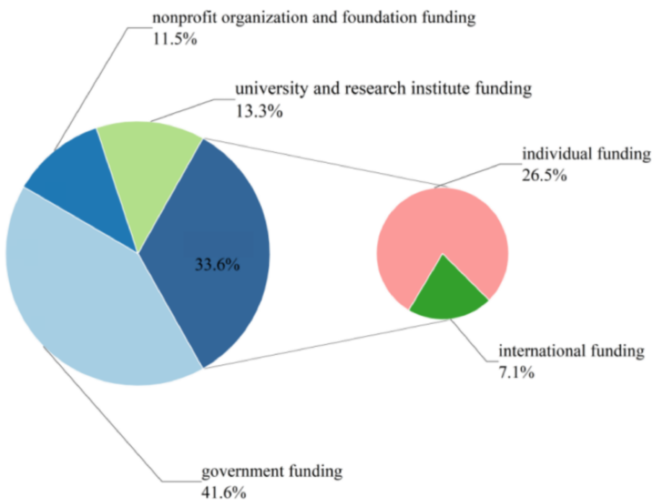
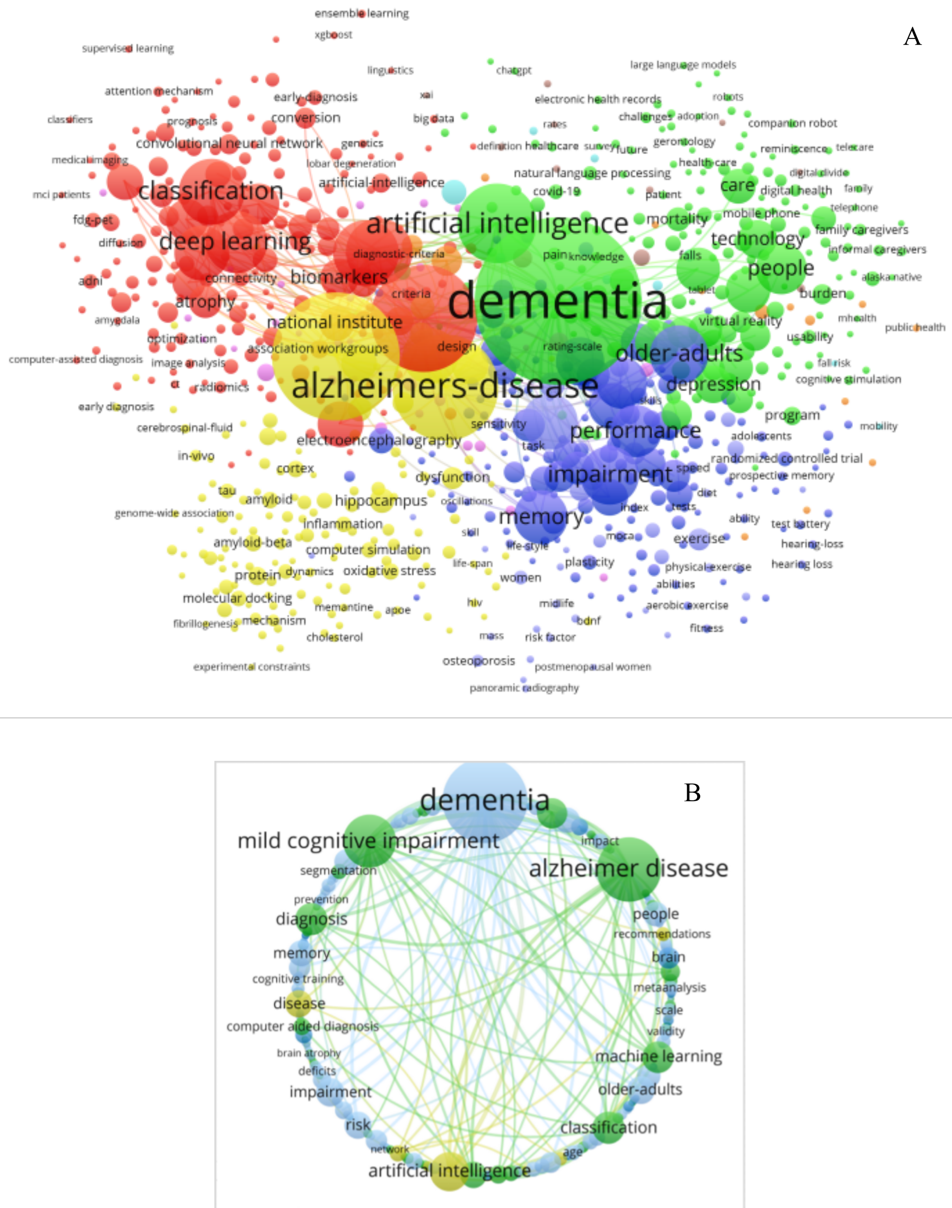


Figure 5. Analysis of funding types for research on nursing care for patients with cognitive impairment assisted by artificial intelligence technology

Table 3. Top ten funding sources for research on AI- assisted nursing care for patients with cognitive impairment

Rank	Grant	Funding Count (N=9317,n%)	Country
1	U.S. Department of Health and Human Services (HHS)	871 (9.4)	United States
2	National Institutes of Health (NIH)	864 (9.3)	United States
3	National Institute on Aging (NIA)	473 (5.1)	United States
4	National Natural Science Foundation of China (NSFC)	300 (3.1)	China
5	Canadian Institute Of Health And Research (CIHR)	169 (4.3)	Canada
6	NIH National Institute of Neurological Disorders and Stroke (NINDS)	160 (1.7)	United States
7	Alzheimer's Association	159 (4.1)	-
8	European Union	157 (4.0)	-
9	National Institute of Biomedical Imaging and Bioengineering (NIBIB)	142 (3.6)	United States
10	UK Research Innovation UKRI	136 (3.5)	United Kingdom



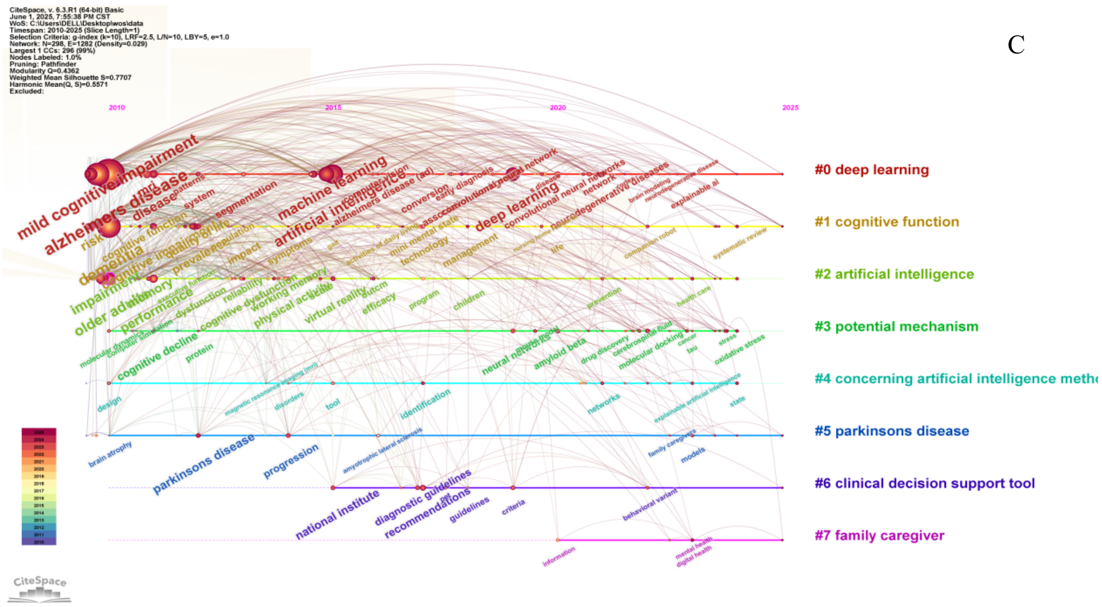


Figure 6. Keyword analysis on research of AI assisted nursing for patients with cognitive impairment. (A). Clustering analysis chart of co linear keywords. Time chart of co-occurrence clustering of keywords; (B). Use color coding to display clusters, where keywords within the same cluster share the same color. (C). Timeline of keyword analysis in the past 15 years.

4.6 Author analysis

The visualization analysis on the author's collaborative network diagram (Figure 7) reveals the characteristics of academic collaboration of AI technology in assisting nursing research on patients with cognitive impairments. The author collaboration network graph constructed by VOSviewer shows that the researcher population in this field exhibits a clear "core edge" structural distribution, with both highly dense collaborative sub networks and several relatively independent research nodes. From the pictures, these research groups mainly exhibit the following significant characteristics: a highly close collaborative cluster formed by scholars such as Kaye Jeffrey and Mattek Nora as the core, with stronger connectivity of nodes, which deeply reflects a long-term stable collaborative relationship between the groups within a specific research team. Therefore, the literature published by this group accounts for the majority of all literature. The academic group composed of scholars such as Petersen Ronald C. and Geda Yonas E. has demonstrated deep collaboration and close connections within their respective fields of expertise. In addition, the sparse node connections between certain groups suggest that there are still obstacles such as geographical isolation or academic differences in cross team collaboration. Therefore, in future research, efforts should be made to address these obstacles and better strengthen the collaboration cross teams.

By analyzing the attributes of nodes, we found that researchers' personal research influence follows a gradient distribution. For example, researchers with larger nodes and high color saturation (such as Kaye Jeffrey, etc.) have a significantly higher literature output and academic collaboration intensity than those scholars at the edge of the collaboration network. It is worth noting that there are also widely distributed small node groups in the entire collaborative network diagram, which not only reflects the diversified characteristics of research topics in this field, but also reflects that some scholars are still in a relatively isolated research state and need to strengthen the academic cooperation and connections between each other. In recent years, with the continuous development of artificial intelligence technology and the increasing financial support from various institutions in society, the intensity of author collaboration in this field has shown a clear upward trend. This cooperation model not only demonstrates that the core research team in this field has established an efficient collaboration mechanism, but also reveals the important value of cross cluster communication in optimizing academic resource allocation.

5. Discussion

Through in-depth analysis of literature output, interdisciplinary collaboration, and collaboration between countries and authors in the field of AI assisted nursing for patients with cognitive impairment, we have gained a comprehensive understanding of the current status of this field and identified some of its challenges and limitations. In order to have a more systematic discussion on these issues, we mainly divide the discussion into three aspects: the current situation in the field, the main challenges

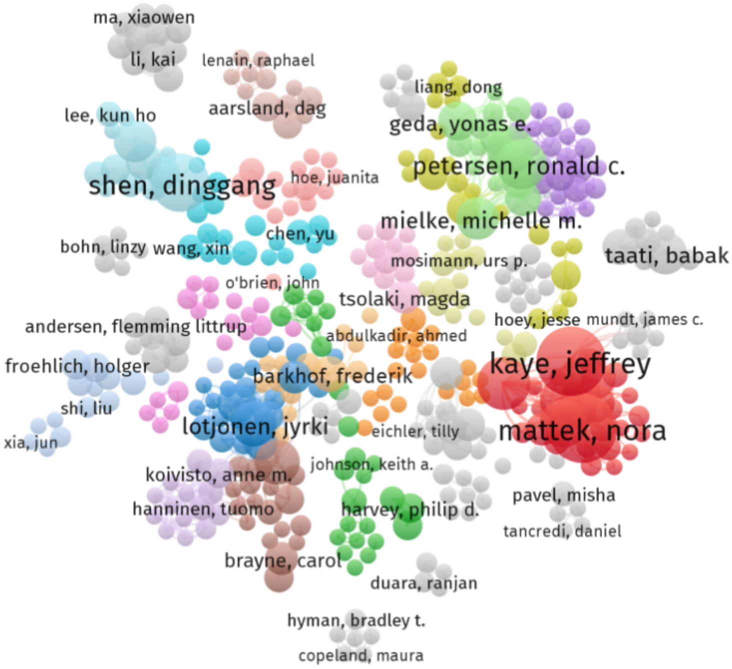


Figure 7. Graph of core authors' collaboration network.

Notes: Color coding is used to display clusters, with authors within the same cluster sharing the same color. The size of the circles increases with the number of publications.

and obstacles faced, and new directions for future development.

5.1 Current applications and clinical integration of AI in cognitive impairment care

Presently, AI technology has formed three collaborative application systems, which are more conducive to effectively optimizing the traditional nursing models.

Firstly, there is an intelligent monitoring systems, which mainly integrate wearable devices with smart home technology to continuously track physiological parameters, sleep quality, and cognitive functions. A search in the Web of Science core database revealed that there were 122,134 articles directly related to the application of smart home integration in cognitive impairment care over the past five years. These studies focus on integrating smart home devices such as smart mattresses, cameras, and door locks with nursing monitoring systems to improve the quality of life for patients with cognitive impairments. A research has confirmed [18] that multi-source data fusion technology can integrate multi-source information from wearable devices, smart home devices, and cognitive assessment tools to identify the characteristic behavioral abnormalities of disease progression in real time. In addition, machine learning algorithms such as support vector machines, decision trees, and neural networks are key technologies for intelligent monitoring systems, used for in-depth analysis and learning of patient behavior patterns. A research [19] shows that its recognition accuracy has improved compared to traditional methods, and the nursing model has shifted from intermittent assessment to continuous monitoring.

Secondly, there is a rehabilitation intervention for patients with cognitive impairment, where adaptive algorithms, personalized cognitive training programs, virtual reality training systems, etc. can adjust training parameters in real-time based on the patients' performance. Research conducted by Tacchino A. et al., [20] shows that this intervention significantly improves the retention efficiency of patients' memory by 22% . In addition, the system can improve patient engagement while also optimizing clinical resource allocation through automated evaluation [21].

Finally, there are psychological and social supports for patients. The use of AI technology in the care for patients with cognitive impairments mainly solves the problem of social isolation through a dual mechanism approach: emotional interaction robots (Pepper et al.) [22] that can provide continuous psychological support for patients. Through intelligent matching systems, we can establish new social networks for patients and fundamentally alleviate their issues caused by social isolation. There are also studies [23] indicating that this intervention can significantly reduce the scores of patients' depression scales ($p < 0.01$) and lower the risk of depression in patients with cognitive impairment. In addition, by integrating natural language processing technologies such as emotion analysis based on speech biomarkers [24], a more objective and quantitative assessment on patients' psychological states can be achieved. The application of artificial intelligence technology in the field of cognitive impairment nursing is gradually developing towards a comprehensive monitoring intervention support system.

However, in order to better achieve the clinical translation of these technologies, the following measures need to be taken: firstly, to establish an interdisciplinary collaborative design mechanism, which plays a crucial role in ensuring seamless integration between technical solutions and clinical workflows [25]; Secondly, to improve the AI skills of specialized nursing staff by training system and enhance the AI literacy of clinical nursing staff [26]; Finally, to establish a more sound framework for data governance and ethical review, which is the foundation for ensuring the sustainable development of technology in the future. Only by overcoming these challenges can we fully leverage the potential value of AI technology in the transformation of care for patients with cognitive impairments.

This study reveals the application characteristics of AI technology in cognitive impairment care. Although the development trend of AI technology in cognitive impairment care is similar to that of generalist medical artificial intelligence (GMAI), both have evolved from single functions to integrated systems [27], there are significant differences in reality: GMAI is committed to building universal solutions across disease domains, while AI technology in cognitive impairment care is limited by algorithm specificity caused by data heterogeneity, and its cross-cultural adaptability and generalization ability have not reached GMAI standards [28].

5.2 The pattern of fund allocation and its profound implications

Research by Barragán-Montero A. et al. [29] indicates that there are still limitations to the generalization ability of artificial intelligence in the field of cognitive impairment care. Although progress has been made in the fields such as medical imaging analysis, its cross-cultural and multi center application performance is unstable due to data bias and algorithm design limitations [30]. This is mainly caused by the heterogeneity of training data and significant individual differences in behavioral data of patients with cognitive impairment, leading to a decrease in cross group generalization ability.

Therefore, in the future, we should focus on developing modular adaptive systems, alleviate the problem of sample limitation through migration learning, and embed interpretable modules (which can increase the recognition rate of mixed dementia by 12% [31]). At the same time, we need to strengthen multimodal data fusion [32], achieve a real-time monitoring [33] in combination with 5G and edge computing, and build a multi center collaboration framework based on federal learning [34] to optimize personalized intervention programs.

We also systematically compared the research results with the development trend of GMAI, revealing the necessity of AI technology for continuous innovation in the field of nursing care for patients with cognitive impairment. Research by Birkenbihl C. et al. [35] indicates that there is still a significant gap in cross domain adaptability and full-process automation of the current technological system. Cross cultural validation research shows that AI models trained on single cultural data have an error rate increase of 15% -20% when applied across regions, highlighting the urgency of strengthening inclusive algorithm design.

In summary, future technological breakthroughs should focus on three directions: firstly, improve data quality and enhance sample diversity through multi center collaboration; secondly, optimize the algorithm architecture and develop modules for cultural sensitive indicators and adaptive features; finally, integrate 5G, edge computing and other technologies to realize the automation of the whole process of monitoring and intervention evaluation. These improvements will drive AI systems to better transform into intelligent care ecosystems. At the same time, it is necessary to ensure that technological development is synchronized with clinical needs. Research [36] has shown that federated learning multimodal systems of intervention evaluation can improve cross-cultural application accuracy by 18%, but still face clinical translation challenges such as ethical review and operational standardization. Therefore, it is necessary to actively establish interdisciplinary collaboration platforms, integrate clinical, data, and ethical expert resources, and promote the standardized development of AI nursing.

The current main obstacle [37] lies in the disconnect between AI tools and clinical workflows, where many solutions are developed without the involvement of nurses, resulting in the system being unable to meet actual needs or increasing clinical burden. Therefore, it is necessary to strengthen the interdisciplinary collaboration among developers, nurses, and geriatric experts to ensure that technology truly serves clinical practice.

5.3 Strategies for overcoming implementation challenges

In order to effectively promote the clinical application of artificial intelligence technology in the care for patients with cognitive impairment, this study suggests starting from three aspects: firstly, to establish a nursing practice oriented mechanism for collaborative development of AI technology [38], which enables clinical nurses to participate in the entire development cycle, and adopt participatory design methods [39] to improve the applicability and matching of technology, reduce unnecessary work, and improve efficiency. Second, to establish a systematic training system for nursing staff to improve their capability of AI technology, covering three core modules, to enhance their technical acceptance and operational accuracy [36]. Third, to establish a diverse collaborative implementation support team that clarifies the composition and proportion of members, focuses on intergating workflow and optimizing system iterations, and to establish a multidimensional effectiveness evaluation system.

Although artificial intelligence has shown great potential in the field of cognitive impairment care, its clinical translation still faces multiple challenges such as technological adaptability, ethical compliance, and economic feasibility. Based on the current research bottlenecks, this study mainly proposes two breakthrough development directions aimed at promoting sustainable development in this field through systematic innovation.

5.3.1 Optimization and application of privacy preserving federated learning framework

The protection of medical data privacy constrains the development of AI technology, and the data collection bias of patients with cognitive impairments exacerbates the challenge. Federated learning (FL), as a distributed machine learning paradigm, provides innovative solutions for cross institutional collaboration attributed by its feature of "data doesn't move, model moves". In the future, a FL ecosystem for cognitive impairment care should be built, so the focus should be on technically optimizing communication protocols to improve multi center training efficiency [40]; Secondly, design a patient friendly data collection interface to reduce data noise. Finally, to clarify data sovereignty and respond to ethical issues by establishing a dynamic informed consent mechanism [41].

5.3.2 Improvement of real-world clinical validation system

There are issues with ideal environment bias in current AI technology research, therefore there is an urgent need to establish a rigorous clinical validation framework, which can be achieved through the following aspects: firstly, conduct multi center, large sample randomized controlled trials (RCTs), incorporate optimization research designs from different medical resource allocation institutions; secondly, establish a multidimensional evaluation system that comprehensively evaluates patients based on indicators such as diagnostic accuracy; finally, strengthen the correlation analysis between patient reported outcomes (PROs) and real-world evidence (RWD) [42]. It is possible to consider establishing a long-term follow-up mechanism by establishing a tracking mechanism of $\geq$ 12 months to evaluate the sustained benefits of technology application.

5.3.3 Systemic challenge response and innovation ecosystem construction

Currently, the application of technology faces three obstacles: firstly, the dilemma of data quality. Elderly patients suffer from inaccurate data collection due to operational barriers, and about 35% of wearable device data is removed due to improper wearing [43]; secondly, there is a cultural adaptability deficiency, with a cross group generalization error of 18-25% for models trained on a single cultural background, which is more significant in applications for ethnic minorities; finally, the existing fall detection system has an average response delay of 1.2 seconds and a false alarm rate of 15%, which is the biggest bottleneck [44].

To address these issues, the following measures can be taken: firstly, establish a multimodal perception system that integrates speech biomarkers to improve data completeness by 40%; secondly, compress the critical response delay within 200ms in the form of 5G+MEC, reduce the false alarm rate below 5%; finally, the deep reinforcement learning framework (DRL) can be used to achieve dynamic optimization of intervention strategies at minute level.

5.3.4 Ethical privacy challenge

The rapid development of generative artificial intelligence models poses significant risks of privacy and may leak sensitive information of training data. At the same time, the widespread use of home monitoring devices can lead to serious disputes on privacy protection, so it is necessary to clarify the boundaries of data collection and use. When artificial intelligence systems make incorrect judgments or omissions, the issue of responsibility attribution is often difficult to clarify. We can solve this problem by establishing a unified industry standard system, clarifying the basic requirements for data security, privacy protection, and clinical efficacy of artificial intelligence nursing products. Research by Ma Z. et al. [45] shows that federated learning can achieve the multi center data of collaborative training, protect privacy, and optimize models. In addition, interpretable artificial intelligence technologies should be developed to improve algorithm transparency.

5.3.5 Economic costs and barriers to popularization

High end artificial intelligence nursing equipment (such as intelligent companion robots) are expensive and difficult to promote on a large scale in ordinary households and elderly care institutions. And the phenomenon of digital divide is obvious, with low acceptance of new technologies among the elderly and insufficient infrastructure in rural and low-income areas. Research by Siriwardhana Y. et al. [46] pointed out that although edge computing and 5G can improve the efficiency of real-time monitoring, the popularity of high cost devices is still limited by the ability of families to pay. To this end, cost can be reduced by developing lightweight applications, promoting the government to include devices in medical insurance reimbursement or providing subsidies, organizing volunteers or family members to provide technical guidance for the elderly, and strengthening the mastery and acceptance of new devices.

In summary, this study aims to lay the foundation for the long-term development of artificial intelligence technology in the field of cognitive impairment care, promoting its safety, effectiveness, and personalization. By exploring collaborative learning frameworks, designing clinical validation studies, and constructing innovative systems, we aim to establish an intelligent nursing ecosystem that balances technological innovation and humanistic care.

6. Conclusion

This study is based on the search in the core collection database of Web of Science, and comprehensively uses bibliometric tools such as VOSviewer and CiteSpace to systematically analyze the current application status, research hotspots, and development trends of artificial intelligence in the field of cognitive impairment nursing. This method objectively and visually presents the research structure and collaborative network in the field, which is more comprehensive and intuitive than traditional reviews, providing important references for subsequent scientific research and clinical practice.

The knowledge graph analysis shows that research on artificial intelligence in cognitive impairment care has entered a rapid development stage, with a continuous increase in literature and increasingly close international cooperations, forming a research network centered around the United States, China, and European countries. In addition, the research topics have gradually expanded from early algorithm development and medical image analysis to multiple cutting-edge directions such as multimodal data fusion, personalized intervention, interpretable artificial intelligence, and the construction of intelligent nursing systems. Currently, this field is moving from technical validation to clinical translation and integrated applications, with a particular emphasis on adaptability, usability, and ethical compliance in real-world environments.

Therefore, future research should further strengthen the interdisciplinary collaboration, promote the deep integration of interpretable AI and clinical workflow, attach importance to data privacy and algorithm fairness, and focus on building a technical framework that supports multi center verification and federated learning. At the same time, attention should be paid to the technological accessibility of resource limited areas and vulnerable groups, and the application threshold should be lowered through policy support and innovative payment mechanisms to promote the inclusive and personalized development of artificial intelligence in cognitive impairment care.

Limitations

While this bibliometric study provides a comprehensive mapping of AI applications in cognitive impairment care, several methodological constraints should be acknowledged. The data source is limited to English literature in the Web of Science core collection database, and does not cover other databases or non English published literature, which may result in the omission of some relevant literature. In addition, the search deadline is June 2025, which makes it difficult to fully reflect the rapid progress of emerging technologies such as generative AI, and bibliometric methods cannot evaluate the quality and clinical efficacy of the original research. Therefore, future research can expand the scope of retrieval and data sources, combine the literature from multi databases and live evidences, further enhance the comprehensiveness and timeliness of analysis results, and provide a more solid basis for the standardized application and policy formulation of artificial intelligence in cognitive impairment nursing.

Appendixes

The appendixes mentioned in this research (Multimedia appendix 1, appendix 2 and appendix 3) are available at https://file.luminescience.cn/JDH-419%20Appendixes.pdf.

Database and language biases

Our analysis was restricted to English-language publications in the Web of Science Core Collection, which may underrepresent research from non-English-speaking regions and exclude relevant studies indexed in other databases. This bias is particularly relevant given our finding that 76.3% of productive institutions are located in English-dominant countries.

Inability to assess research quality

Bibliometric indicators (e.g., citation counts, publication volume) cannot evaluate the methodological rigor or clinical efficacy of included studies. Besides, our methods could not verify their adherence to the guidelines of Consolidated Standards Of Reporting Trials (CONSORT) or clinical significance.

Temporal lag in emerging technologies

The cutoff date (June 13, 2025) may not capture the rapid advancements in generative AI applications, as evidenced by the low frequency (9 occurrences) of terms such as "GPT" or "large language models" in our keyword analysis.

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Authors' contributions

SZ conceived this research, formulated research methods, conducted the data visualization, and edited the manuscript. XZ was responsible for the methodology and wrote the first draft. YJ collated data and formulated research methods. SC conceptualized this research, reviewed and edited the manuscript, obtained funds, managed the project, and conducted a formal analysis. HS provided software and other resources and set research methods. XL and QP conducted formal analysis and supervision. All authors reviewed the draft, provided comments and revisions, and approved the final version of this manuscript.

Conflict of interest

The authors declare that there is no conflict of interest in this work.

Ethical consideration

No ethical approval and patient consent were required for the analyses in this work.

Ethics approval and consent to participate

Not applicable.

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