



在线全文

人工智能与长寿医学交叉研究: 全球格局、合作网络与前沿趋势 (2010–2025)

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【摘要】目的 随着衰老理论的拓展与人工智能(AI)方法学的快速演进, AI与长寿医学的交叉融合已成为延长人类健康寿命的关键路径。本研究旨在系统揭示该交叉领域的研究格局、合作网络与前沿趋势, 为其临床转化与健康管理产业发展提供依据。**方法** 本研究以 Web of Science 核心合集(SCIE+SSCI)为数据源, 系统检索2010–2025年间AI与长寿医学交叉领域的英文文献, 共纳入4 170篇有效文献, 采用Bibliometrix与CiteSpace 7.0联合分析策略。**结果** 该领域发文量呈指数型增长; 全球格局形成中美双核心、多极化态势, 机构合作划分为亚欧、美国与欧陆三大网络; 研究主题汇聚为衰老与多病共存核心概念、AI驱动的身体成分与肌骨评估、深度学习驱动的神经影像衰老评估、可穿戴传感与移动健康、数字表型与心理健康五个研究主题聚类; 中、美、英三国研究侧重点存在明显差异: 中国呈广覆盖、临床导向多线并进特征, 美国深耕方法学与数字表型, 英国聚焦于脑龄方向。**结论** 本研究系统勾勒出AI与长寿医学交叉领域的研究格局、合作网络与前沿趋势, 可为该领域的临床转化及健康管理产业发展提供数据支撑与决策参考。

【关键词】 人工智能 长寿医学 老年科学 衰老生物标志物 脑龄 数字表型 CiteSpace

Interdisciplinary Research on Artificial Intelligence and Longevity Medicine: Global Landscape, Collaboration Networks, and Frontier Trends (2010–2025)

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[Abstract] Objective With the expansion of theories concerning aging and the rapid evolution of artificial intelligence (AI) methodologies, the integration of AI and longevity medicine has emerged as a critical pathway for extending human healthspan. This study is aimed at a systematic characterization of the research landscape, collaboration networks, and frontier trends in this interdisciplinary field, so as to inform clinical translation and the development of the health management industry. **Methods** The Web of Science Core Collection, including Science Citation Index Expanded (SCIE) and Social Sciences Citation Index (SSCI), was used as the data source. English-language publications in the interdisciplinary field of AI and longevity medicine between 2010 and 2025 were systematically retrieved, and 4 170 valid records were included for a joint analysis using Bibliometrix and CiteSpace 7.0. **Results** Annual publication output showed exponential growth. The global research landscape exhibited a China–US dual-core and a multipolar pattern, with institutional collaborations clustering into 3 major networks spanning Asia–Europe, the United States, and Continental Europe. Research topics were clustered into five major themes—the core concepts of aging and multimorbidity, AI-driven body composition and musculoskeletal assessment, deep-learning-based evaluation of brain aging through neuroimaging, wearable sensing and mobile health, and digital phenotyping and mental health. Marked differences in research priorities were observed among the three leading contributors, including China, the United States, and the United Kingdom. China demonstrated broad research coverage and clinically oriented multi-track development, the United States led in methodological innovation and digital phenotyping, and the United Kingdom concentrated on brain age research. **Conclusions** This study systematically delineates the research landscape, collaboration networks, and frontier

trajectories in the interdisciplinary field of AI and longevity medicine, providing data-driven evidence and decision-making support for advancing clinical translation and the development of the health management industry in this field.

[Key words] Artificial intelligence Longevity medicine Geroscience Aging biomarkers Brain age Digital phenotyping CiteSpace

现代衰老研究的科学化始于19世纪末, 经过逾一个世纪的演进, 2013年López-Otín 等^[1]提出衰老九大标志, 2023年拓展至12个标志, 进一步完善了衰老的系统生物学图景^[2]。Kennedy 等^[3]据此系统阐述了老年科学(geroscience)假说, 主张靶向衰老核心机制有望同步延缓多种年龄相关疾病。Bischof等^[4]进一步提出基于衰老深度生物标志物进行的生物学年龄诊断与个性化干预应从成年中期即开始, 以延长健康寿命, 长寿医学(longevity medicine)应运而生。2025年, Kroemer 等^[5-6]提出以高通量组学、临床与数字衰老生物标志物为基础, 结合个体遗传与心理社会暴露评估, 构建精准长寿医学策略。目前, 长寿医学已不局限于对老年群体疾病发生后进行干预, 而是覆盖生命全周期, 在疾病发生前进行风险预测并进行干预, 从而实现健康寿命的整体延长。

随着机器学习的发展, 基于机器学习构建的血液生化衰老时钟, DNA甲基化衰老时钟等在预测衰老相关疾病风险中展现出显著的应用前景^[7-8]。近年来, 基于人工智能(artificial intelligence, AI)算法构建的脑龄^[9]、视网膜年龄^[10]等器官衰老指标, 与基于代谢、免疫、微生物组等构建的衰老评估模型结合, 构成长寿医学的多维指标体系。本研究基于Web of Science(WoS)核心合集, 对2010–2025年间人工智能与长寿医学交叉领域的英文文献进行系统检索与分析, 采用Bibliometrix与CiteSpace 7.0联合分析策略, 全面描绘该领域的研究景观、合作网络、主题聚类与前沿方向, 为其临床转化提供数据基础。

1 资料与方法

1.1 数据来源与检索策略

以WoS核心合集中的SCI-Expanded与SSCI为数据来源, 检索于2026年3月31日执行。采用主题检索(TS)策略, 最终检索式由两个主题集的布尔AND组合构成。

主题集1(AI方法学): 涵盖人工智能(artificial intelligence)、机器学习(machine learning)、深度学习(deep learning)、神经网络(neural network)等AI核心术语。主题集2: 由于长寿医学作为新兴学科, 涵盖范围远超寿命(longevity)或抗衰老(anti-aging)的传统术语, 本研究采用了广义关键词扩展策略, 将检索式从基础老年生物学扩展到精准长寿医学, 具体包括: (1)衰老核心概念: 长寿医学(longevity medicine)、健康寿命

(healthspan)、老年科学(geroscience)等; (2)多组学衰老时钟: 表观遗传时钟(epigenetic clock)、蛋白质组时钟/年龄(proteomic clock/age)、转录组时钟/年龄(transcriptomic clock/age)、代谢时钟/年龄(metabolomic clock/age)等; (3)器官特异性衰老时钟: 脑龄(brain age)、视网膜年龄(retinal age)、心龄(heart age, cardiac age)、心电图年龄(ECG age)、动脉年龄(vascular age)、面部年龄(facial age)等; (4)衰老生物标志物及机制: 衰老标志物(hallmarks of aging)、细胞衰老(cellular senescence)等; (5)其他: 代谢健康老龄化、微生物组与免疫衰老、数字健康与干预手段。完整检索式见网络资源附表。

1.2 纳入与排除标准

纳入标准: 发表年份限定2010–2025年; 文献类型限定为Article与Review; 语言限定为英文。初步检索获得6 678篇文献, 限定时间范围后剩余6 049篇, 限定文献类型后剩余4 965篇(其中Article 4 430篇、Review 535篇)。随后依据WoS学科分类排除与研究主题无关的领域, 学科分类详细纳入排除标准见附录。

数据清洗: 由于本领域标题多含机器学习、脑龄等高频词, 检测阈值过低会误检文献、过高则可能漏检重复文献, 故Bibliometrix端以标题为字段、采用默认阈值0.95判重; CiteSpace端独立执行按标题、作者、来源、年份等书目字段匹配检测的内置去重程序。两平台均最终保留4 170篇, 结果一致。文献筛选流程见图1。

1.3 分析工具与方法

采用Bibliometrix与CiteSpace 7.0联合分析策略, R语言端完成年度趋势、高产国家与机构的描述性统计; 国家间合作、机构合作及关键词共现网络采用Louvain算法进行社区聚类, 绘制国家-关键词差异化布局图。CiteSpace完成关键词突发性检测, 关键词时间线可视化。CiteSpace主要参数设置: 以LLR算法标记聚类, 主题时间切片1年; g-index(k=15); LRF=-1.0; L/N=10; LB=5; e=50.0; 不剪枝。

2 结果

2.1 年度趋势与全球分布

年度发文量呈指数型增长(图2A)。2010至2015年累计不足60篇, 2016年起持续加速, 2021年后爆发式上升, 2025年单年达1 341篇。

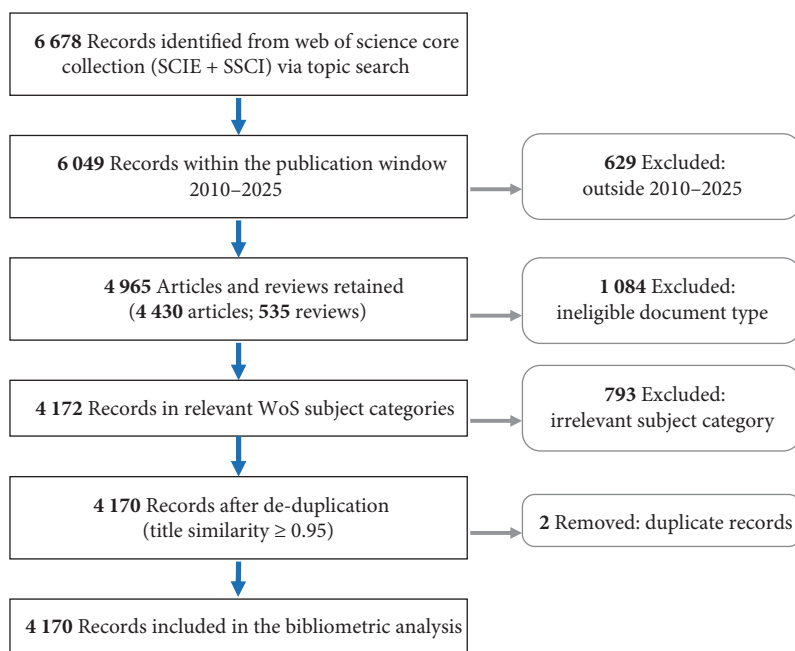


图 1 文献筛选 PRISMA 流程图

Fig 1 PRISMA flow diagram of the study selection process

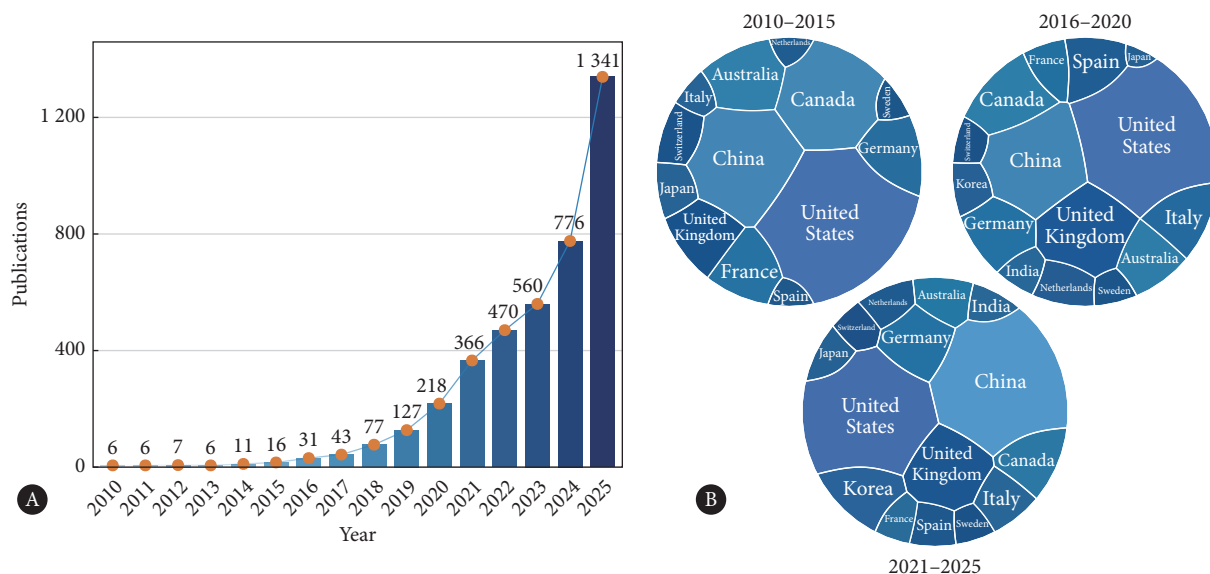


图2 年度发文趋势与国家/地区分布

Fig 2 Annual publication trends and country/region distribution

A: Annual publication output in 2010–2025; B: evolution of national output shown as Voronoi treemaps for three periods (2010–2015, 2016–2020, and 2021–2025).

全球格局呈三阶段演变(图2B)。2010-2020年美国略占优势、中国紧随,2021-2025年确立中美双核心,韩国、德国、英国、印度等多国共同构成多极格局。中国由紧随跃至与美国并列核心,反映其快速、大规模投入应用的AI产业,在长寿医学领域快速追平美国的方法学先发优势。

Louvain算法将国家间合作网络划分为两个主要社群(图3):以中、美、加、韩、澳、日、印度为核心的亚太-

北美集群(簇1),以英、德、意、法、瑞士、荷兰、西班牙、北欧诸国为核心的欧洲集群(簇2)。中美、美英的双边合作最为密切,而美国同时与两大集群保持高强度连接,是衔接亚太与欧洲的枢纽。

2.2 高产机构与合作聚类

高产机构划分为3个主要社区(图4A)。簇1为中欧学术合作网络,整合了中国与英国主导的众多机构。簇2为美国学术合作网络,以哈佛体系、加利福尼亚大学系统等

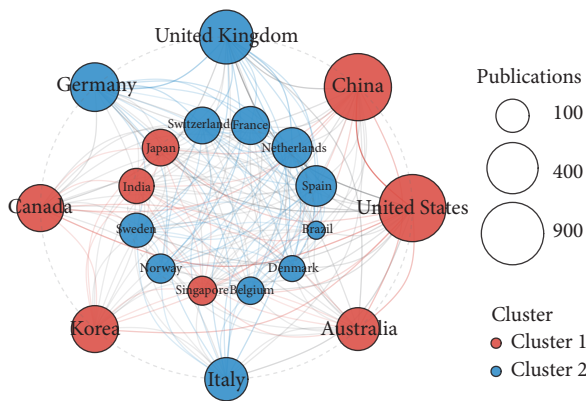


图3 基于Louvain算法的国家间合作网络聚类

Fig 3 Clustering of the inter-country collaboration network based on the Louvain algorithm

The network is partitioned into two community by the Louvain algorithm; the node size denotes publication output and the colors denote the communities of core. Cluster 1 is the European research network, with Germany and France as the core.

High-product institutions on the list, Harvard University (208 articles) ranked first, followed by the University of California system (177 articles), Harvard Medical Institutions (171 articles), and London University (153 articles), Harvard Medical School (134 articles) (Figure 4B). Among the top 10 institutions, the United States occupies six and belongs to the same community, while London University is the only non-American institution to enter the top five, showing that the United States has a high degree of internal aggregation, with the single-point突出 of the United Kingdom as a contrast.

2.3 主题聚类、突发与时间线演变

Louvain algorithm divides the keyword co-occurrence network into five thematic clusters (Figure 5A). Cluster 1 is aging and multi-disease co-occurrence core concept group, containing aging

old, elderly population, cell aging, Alzheimer's disease, cancer, cardiovascular diseases; Cluster 2 is AI-driven body composition and bone assessment, containing muscle atrophy, body composition, computer tomography, osteoporosis, obesity; Cluster 3 is deep learning-driven neuroimaging aging assessment, containing deep learning, brain age, magnetic resonance imaging, neuroimaging, convolutional neural network, feature extraction; Cluster 4 is wearable sensing and mobile health, containing wearable sensors, wearable devices, mobile health, computer vision; Cluster 5 is digital phenotype and mental health, containing digital phenotype, digital health, mental health, depression, etc.

Keyword burst detection (Figure 5B) shows a clear evolutionary trajectory. From 2010 to 2017, the research focuses on cortical thickness, classification, algorithms, accelerometers, activity recognition, lifespan, etc. Basic methodology and neuroanatomical indicators were the main focus; from 2017 to 2018, the research shifted to facial age estimation, convolutional neural networks, age prediction, fall detection, mobile phones, gait, big data, etc. High-intensity keywords, marking the large-scale introduction of deep learning and wearable, mobile technology; from 2019 to 2021, schizophrenia, digital phenotype, prediction, neural networks, mental health, etc. emerged, reflecting the rapid rise of digital phenotype and mental health direction; from 2022 to 2025, the research shifted to mortality rate and cell, etc. A few terms continued to emerge, indicating that the field has moved from early methodology exploration to application deepening stage.

CiteSpace timeline diagram (Figure 5C) further归纳出六个相互关联的成熟聚类 (Modularity $Q = 0.4085$, Mean Silhouette $S = 0.7697$), 按聚类规模依次为 肌少症、细胞衰老、数字表型、脑龄、跌倒检测、机器学习。

Louvain-based module optimization, CiteSpace-based keyword co-occurrence

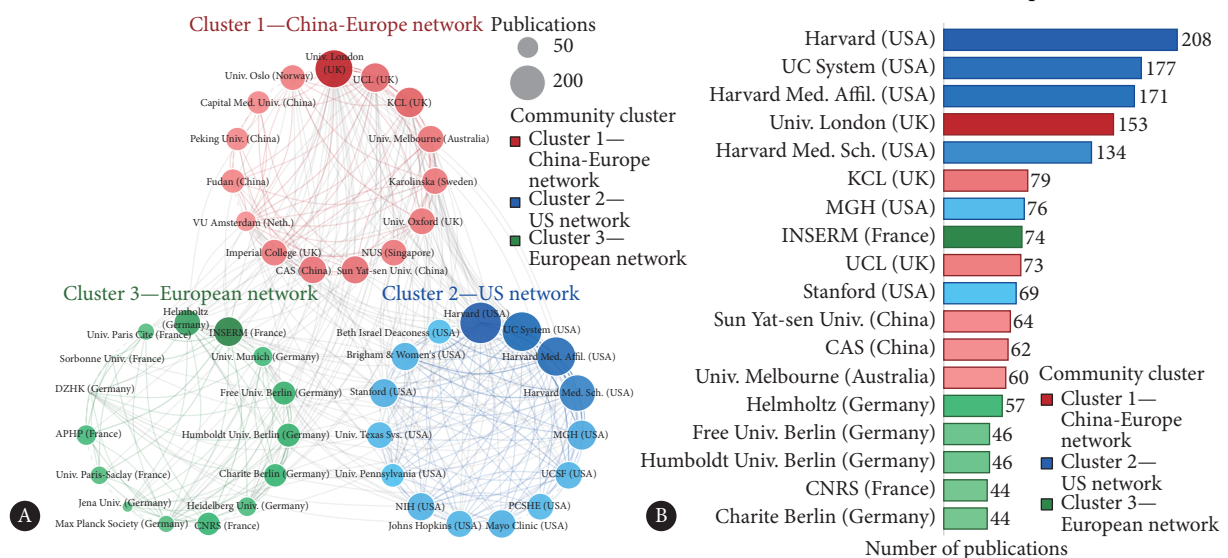


图4 高产机构与合作聚类

Fig 4 High-output institutions and collaboration clusters

CAS: Chinese Academy of Sciences; CNRS: Centre National de la Recherche Scientifique (French National Centre for Scientific Research); INSERM: Institut National de la Santé et de la Recherche Médicale (French National Institute of Health and Medical Research); KCL: King's College London; MGH: Massachusetts General Hospital; UC System: University of California System; UCL: University College London. A: Louvain-based collaboration network of the 300 most productive institutions, partitioned into a China-Europe network (cluster 1), a US network (cluster 2), and a European network (cluster 3); B: the top 18 institutions ranked by publication output and their community membership.

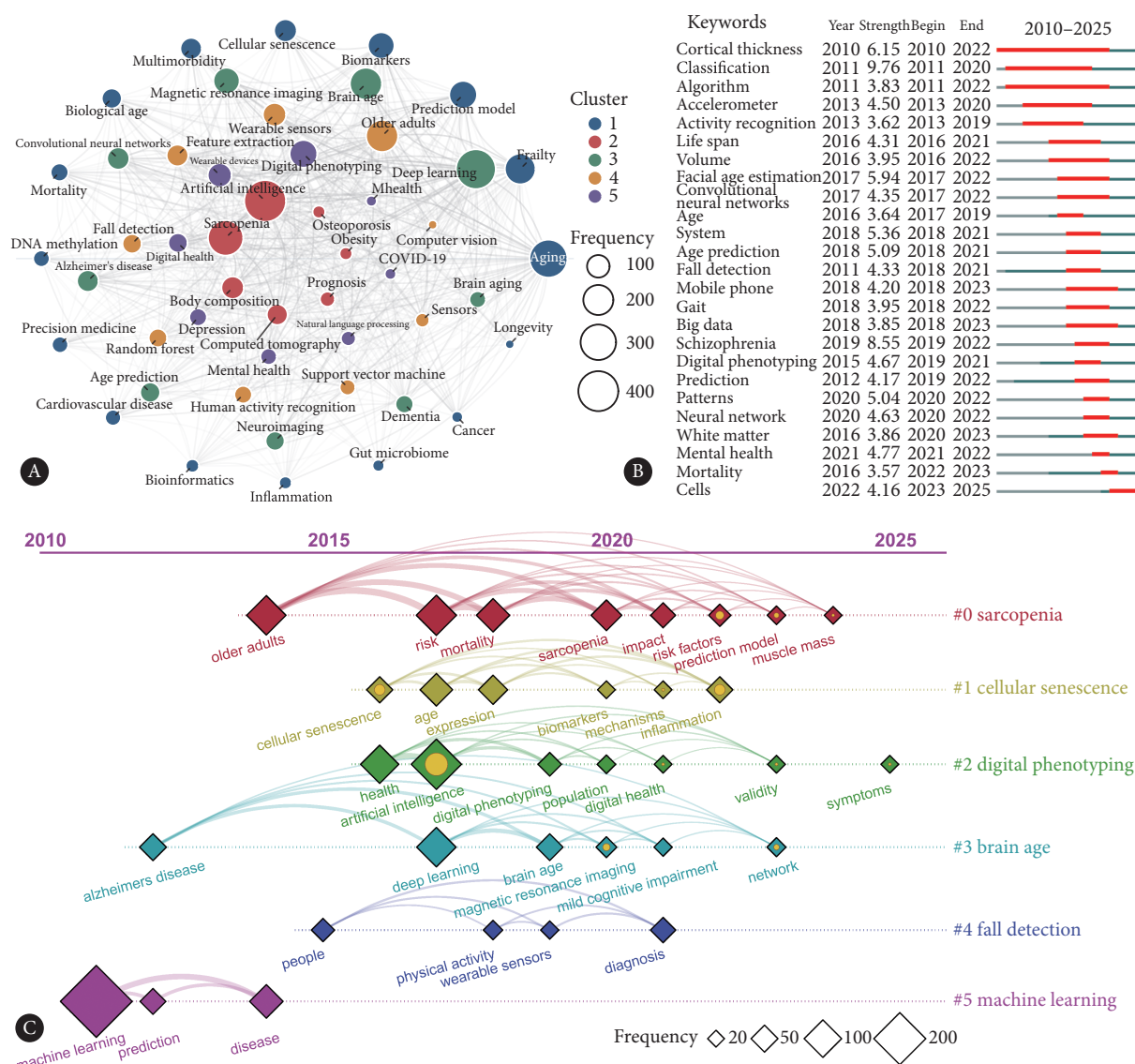


图 5 主题聚类、突发与时间线演变

Fig 5 Thematic clustering, burst detection and timeline evolution

A: Louvain-based keyword co-occurrence network (5 clusters); B: top 25 keyword burst detection by CiteSpace, showing the onset, end, and strength of each burst; C: CiteSpace keyword timeline with clusters labelled by the log-likelihood-ratio (LLR) algorithm.

网络与LLR标签,虽然聚类参数设置及边权重计算方式存在差异,但所得主题方向高度一致(表1)。

2.4 国家差异化研究布局

以中国、美国、英国三个核心国家的高频关键词绘制国家-关键词放射图(图6),可见清晰的差异化特征。中国关键词覆盖最广,机器学习、深度学习、肌少症、衰老、老年人群构成第一梯队,脑龄、人工智能、细胞衰老、预测模型、生物标志物、衰弱、磁共振成像等紧随其后,呈现广覆盖、临床导向的多线并进态势。美国偏向方法学与数字表型,其人工智能频数远高于中国,数字表型在美国排名第五却未进入中国前十,显示美国在这一新兴方向的领先布局,脑龄、衰弱、可穿戴设备、阿尔茨海

默病亦为其活跃方向。英国分布最集中,脑龄占其关键词出现次数的比例为三国之最(约9.7%,中国约5.9%,美国约6.3%),叠加磁共振成像与神经影像双双跻身前列,凸显英国向AI驱动的神影像衰老评估的显著倾斜。三国的侧重差异,实质是各自疾病负担、数据禀赋与政策导向在研究前沿上的投影。

3 讨论

本研究联合使用功能互补的两种分析工具, Bibliometrix 基于 R 语言可复现流程,在描述性统计、共现网络社区聚类,可视化相关领域结构特点以及合作格局方面具有优势; CiteSpace 适用于突发性检测与时间线动态分析,可

表 1 Louvain与CiteSpace聚类结果对照

Table 1 Correspondence between Louvain co-occurrence clusters and CiteSpace timeline clusters

Louvain co-occurrence cluster (Fig 5A)	CiteSpace cluster (Fig 5C)	Shared thematic focus	Representative keywords
Cluster 1: Aging and multimorbidity core concepts	#1 cellular senescence	Aging mechanisms and age-related disease	cellular senescence; biomarkers; Alzheimer's disease; cancer; cardiovascular disease
Cluster 2: AI-driven body composition and musculoskeletal assessment	#0 sarcopenia	Sarcopenia and body-composition AI screening	sarcopenia; body composition; computed tomography; osteoporosis; muscle mass
Cluster 3: Deep-learning-based neuroimaging aging evaluation	#3 brain age	Neuroimaging-based brain-age assessment	deep learning; brain age; magnetic resonance imaging; neuroimaging; mild cognitive impairment
Cluster 4: Wearable sensing and mobile health	#4 fall detection	Wearable and mobile-health applications	wearable sensors; wearable devices; physical activity; fall detection
Cluster 5: Digital phenotyping and mental health	#2 digital phenotyping	Digital phenotyping and mental health	digital phenotyping; digital health; mental health; depression
Methodology dispersed across clusters	#5 machine learning	Early methodological foundation	machine learning; prediction; classification

Because the two algorithms differ in edge weighting and boundary assignment, a few peripheral keywords (e.g., Alzheimer's disease, older adults) may fall into different clusters across the two panels.

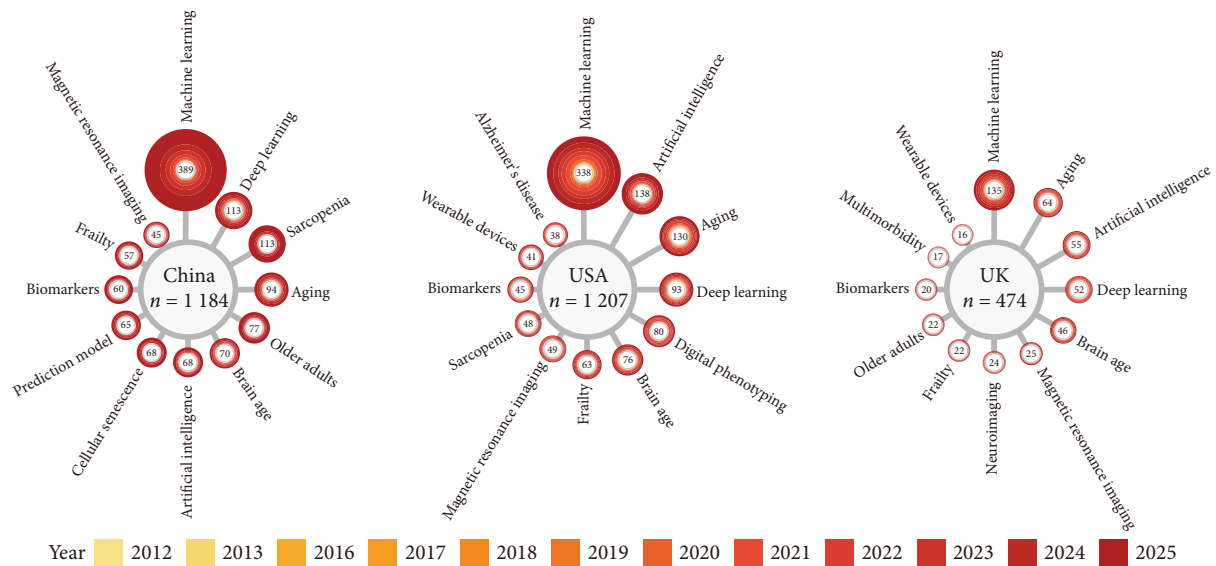


图 6 中国、美国、英国三国高频关键词差异化布局放射图

Fig 6 Radial layout of high-frequency keywords for China, the United States, and the United Kingdom

Each country is centred on its total publication output, with the top keywords and their frequencies arranged radially; the color is graded by the year in which each keyword first appeared.

揭示研究前沿与演进,并借助对数似然比标签自动提炼主题。同时,两者采用不同算法所得主题方向高度一致,形成交叉验证,增强了结论稳健性。

3.1 增长动因与全球格局

本研究观察到的指数型增长曲线呈现三时段特征:2010–2015年萌芽期、2016–2020年持续加速期、2021年以来爆发期。2016年前后正值首个深度衰老时钟提出与深度学习方法在生物医学影像、组学数据中取得突破的窗口期^[7];2020年前后既是 COVID-19 疫情冲击老年人群的时段^[11],也是深度生物标志物研究密集涌现的时段;2023–2025年大语言模型在医学领域的快速渗透^[12]、衰老标志框架的扩展更新^[2]与器官特异性衰老时钟概念的成熟同步发生。中美双核心格局中,美国先发优势源于 AI 技术^[13]、老年科学与大型纵向队列的历史积淀^[14],中国快

速崛起则基于老龄化人口的迫切需求与庞大的影像/电子病历数据资源^[15],英国发挥连接欧美集群的桥梁作用并在脑龄方向具备领先地位。

3.2 长寿指标体系的多维构建

该领域围绕着构建可预测、可解释、可干预的衰老评估体系,目前正沿四条路径并行推进。AI驱动筛选分子标志物路径机制特异性最强^[8],对应聚类1与#1(细胞衰老),但依赖专门的组学检测,难以规模化。影像时钟路径用深度学习从常规影像读取器官生物学年龄^[16],对应聚类3与#3(脑龄),兼顾非侵入与可解释,最适合大规模筛查。功能与身体成分路径以肌少症与 CT 身体成分分析为代表,对应聚类2与#0(肌少症),最贴近现行诊疗流程,临床转化最快。数字表型与可穿戴路径借移动与可穿戴设备把评估推向日常场景^[17],对应聚类4、5与#2、

#4。这些机制层级各异、应用场景互补,最终实现延长群体健康寿命的目的。

3.3 国际差异化布局

中国研究热点紧贴临床筛查。我国3.1亿老年人口^[18],对肌少症、衰弱、多病共存等筛查需求迫切^[19-20]。庞大的CT与电子病历数据加上快速迭代的AI能力,使身体成分自动分析^[21-22]、视网膜年龄^[10]等影像筛查方向率先落地。《“健康中国 2030”规划纲要》与《“十四五”健康老龄化规划》把资源导向可规模化的基层筛查工具,促进中国研究热点实现广覆盖、临床导向^[23-24]。

美国的优势在方法学源头。表观遗传时钟、深度衰老时钟等核心范式多由美国团队提出,方法学的关键词强度亦远高于中、英,背后是老年科学的长期投入、大型纵向队列与长寿生物技术产业的资本驱动。英国脑龄研究独树一帜,既源于Cole等^[25]的开创性工作,更依托UK Biobank等大规模影像-遗传队列的训练数据,从而实现从常规脑MRI精准预测大脑生物学年龄,并以脑龄差量化脑衰老、预警认知衰退与神经退行性变^[26]。

3.4 临床转化与健康管理产业前景

以肌少症为核心的身体成分分析方向呈现出较为完整的临床转化链条^[27]。利用U-Net与Attention U-Net等深度学习语义分割网络,在常规影像学结果中自动识别并分割骨骼肌、脂肪等组织比例,以实现肌少症等疾病的筛查在常规体检流程中即可进行,具有显著的应用前景^[28]。借助卷积神经网络从影像学结果中预测大脑生物学年龄,并经由AI算法提升精度与可解释性的方法学范式,近年来已逐步拓展至眼底彩照、单导联心电图等低成本硬件,使AI驱动的器官衰老评估有望向基层机构渗透^[29-30]。通过可穿戴设备采集并分析个体数字表型是直接面向消费市场的研究分支。通过长短期记忆网络或Transformer等时序深度模型处理智能手环、智能手机所被动采集的步数、心率变异、睡眠分期与活动节律等高频信号,可输出生物学年龄加速度或衰弱风险等综合指标,从而推动健康管理服务从医疗机构向日常生活场景延伸^[17]。此外,借助生成式人工智能与神经网络对衰老相关通路靶点进行挖掘,结合大规模化合物库的虚拟筛选,可显著缩短抗衰老药物的研发周期,并为长期临床队列研究提供有价值的补充^[31]。

3.5 局限性

本研究局限包括:(1)以WoS核心合集为数据源,可能造成对非英语国家研究贡献的低估;(2)Louvain聚类与CiteSpace聚类对参数设置敏感,聚类结果应视为相对划分;(3)仅能呈现时序与共现的相关性。但本研究所采

用的双平台联合分析策略与广义关键词扩展检索式,在最大程度上保证了数据的代表性与结果的稳健性,所识别出的研究格局、合作网络与前沿主题,仍能为理解AI与长寿医学交叉领域的发展态势、判断未来研究方向与推动临床转化和健康管理产业落地,提供可靠的数据支撑与决策参考。

3.6 结论

本研究通过系统分析4170篇2010–2025年间AI与长寿医学交叉领域的英文文献,发现AI与长寿医学的交叉在16年间从萌芽走向爆发,形成中美双核心、多极化的全球格局。研究主题涵盖衰老与多病共存核心概念、AI驱动的身体成分与肌骨评估、神经影像衰老评估、可穿戴传感与移动健康、数字表型与心理健康五大方向。该领域正沿分子、影像、功能、行为四条路径把衰老转化为可测、可解释、可干预的临床指标,机器学习是贯穿其间的共同方法学基础。最高产的中美英三国的研究侧重点存在明显差异,中国凭借庞大的老龄化需求、影像与电子病历数据及《“健康中国 2030”规划纲要》《“十四五”健康老龄化规划》等政策导向,快速推动AI从方法学走向应用层面;美国深耕数字表型与方法学;英国聚焦于脑龄研究。研究结果有望为长寿医学的临床转化与健康管理产业发展提供数据支撑。

* * *

作者贡献声明 黄心言负责论文构思、数据审编、正式分析、软件、可视化和初稿写作,谭建淑负责数据审编、调查研究和验证,曹叔琴,狄隆康和康伦维负责软件和监督指导,朱卓立负责研究方法、提供资源和审读与编辑写作,廖生负责经费获取、研究方法、研究项目管理、提供资源和审读与编辑写作。所有作者已经同意将文章提交给本刊,且对将要发表版本进行最终定稿,并同意对工作的所有方面负责。

Author Contribution Huang Xinyan is responsible for conceptualization, data curation, formal analysis, software, visualization, and writing--original draft. Tan Jianshu is responsible for data curation, investigation, and validation. Cao Shuqin, Di Longkang, and Kang Lunwei are responsible for software and supervision. Zhu Zhuoli is responsible for methodology, resources, and writing--review and editing. Liao Ga is responsible for funding acquisition, methodology, project administration, resources, and writing--review and editing. All authors consented to the submission of the article to the Journal. All authors approved the final version to be published and agreed to take responsibility for all aspects of the work.

利益冲突 所有作者均声明不存在利益冲突

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