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REVIEW

Evolution of Research on Artificial Intelligence for Heart Failure: A Bibliometric and Visual Analysis

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Purpose: To investigate the role of artificial intelligence in enhancing precise diagnosis, personalized treatment, and efficient monitoring of heart failure over the past two decades and to predict future advancements of these investigations.

Methods: A literature search was conducted using keywords from the Web of Science database from January 1, 2004, to August 31, 2024, and 684 articles were retrieved. Bibliometric and visual analysis was conducted to examine annual publication volume; and to analyze authors, institutions, countries, journals, references, and keywords. The following tools were utilized for the analysis: Citespace, SCImago Graphica, Microsoft Office Excel, VOSviewer, and Pajek.

Results: The 684 retrieved studies comprised 70 countries/regions, 1550 institutions, and 4610 authors. The annual publishing output increased gradually between 2004 and 2016, and escalated significantly beyond 2017, particularly from 2021 to 2024. This upward trend is anticipated to persist in the future. Sengupta, Partho P., and Shah, Sanjiv J. were the most productive authors. The University of California and Harvard University were the leading institutions in the number of publications within this discipline. The primary nations conducting research in this domain are China and the United States; the United States predominates research impact and global collaboration. Moreover, Frontiers in Cardiovascular Medicine is the leading journal with the most articles published in this area, while Circulation ranks the highest in co-citations. The keywords include HF, machine learning, AI, and diagnosis.

Conclusion: The application of AI in HF is a global concern in research. Currently, investigations address AI-enhanced HF diagnosis and risk assessment; AI-powered personalized treatment strategies, remote patient monitoring, multi-omics data integration, and HF mechanisms. Predictably, optimizing the use of AI in the ICU and Multimodal data are future trends in research, with AI substantially facilitating effective management of HF.

Keywords: heart failure, artificial intelligence, bibliometrics, machine learning, hot topics

Introduction

HF is an intricate condition attributed to abnormal alterations in cardiac anatomy and performance leading to degraded ventricular diastolic or impaired systolic ventricles.[1] It is primarily characterized by fatigue, shortness of breath, and fluid accumulation, which commonly manifests as peripheral edema, systemic congestion, or pulmonary congestion.[2] The high mortality rate associated with heart failure remains a significant concern. Studies indicate that the 5-year survival rate for patients with heart failure ranges from 54.0% to 59.4%, while the 10-year survival rate ranges from 24.0% to 46.8%.[3] In 2019, 56.19 million people were diagnosed with HF globally.[4] The prevalence of HF is predicted to escalate as the population ages due to escalating average blood pressure and elongated human life expectancy in the coming decades.[5,6] HF is a critical risk to human health that poses a substantial economic burden on the healthcare system.[7] Projections indicate that the healthcare costs associated with HF patients in the United States will be approximately US$69.8 billion by 2030.[8] Therefore, inventing precise and efficient diagnostic approaches as well as implementing personalized treatment plans will ensure efficient prognosis and prevention of HF.

Artificial intelligence (AI) is a technological advancement that emulates human cognitive functions enabling computer systems to execute intricate tasks such as learning, reasoning, self-correction, and environmental adaptation

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to assist or substitute human involvement in decision-making and problem-solving. The use of AI in the medical discipline was first discovered in the 1950s; the investigations identified remarkable benefits and substantial implementation of this technique in the field.[9] In recent years, AI has been integrated into cardiovascular medicine, demonstrating its utility in disease diagnosis, treatment strategies, risk evaluation, clinical management, and the development of pharmaceuticals. Machine learning (ML), is an essential branch of AI that enables systems to autonomously learn from data and enhance their performance through experience, without explicit programming.[10] It involves two main categories: supervised learning, which predicts unknown situations based on pre-existing labeled data and unsupervised learning, which identifies potential patterns within the data without explicit guidance.[11] Studies demonstrated that ML could detect and evaluate HF through echocardiograms and electrocardiograms (ECGs) analysis.[12] Deep learning (DL), an advanced form of ML, employs deep neural network structures to parse complex data, demonstrating remarkable efficacy in areas such as image recognition. AI integrates patients' genetic information, lifestyle, and medical records based on large data and machine learning models to provide personalized cardiovascular risk prediction and assist doctors in implementing therapeutic strategies. It is essential in early warning systems, medicinal management, planning of surgical procedures, and remote monitoring that generates novel strategies for the avoidance, detection, and therapeutic strategies of cardiovascular diseases (CVDs).

Bibliometric analysis is a widely recognized systematic scientific approach employed to investigate extensive quantities of scientific data. It enables comprehensive discovery of advancements in the discipline, highlighting and illustrating novel research trajectories in the field.[13] This method aims to reveal the dynamic development trends of scientific research by systematically measuring the volume of literature, the number of authors, and the frequency of vocabulary usage.[14] Bibliometric methods examine quantitative attributes of the publications and explore the usage patterns of terms or subject terms, as well as the complex connections between researchers and the academic community.[15] Research methods of bibliometric analysis include emergence detection, cluster analysis, co-occurrence analysis, and citation network analysis. These methods provide a substantial foundation for comprehending the structural framework, development trajectory, and impact in academic fields. To date, research efforts primarily concentrated on the overview of heart diseases or the discussion of AI technologies.[16] However, information addressing the scientific quantitative analysis of AI applications in HF is insufficient. Therefore, this study collected relevant data from the databases over the past two decades, thoroughly analyzed the status and progression of AI applications in the HF discipline, and efficiently visualized the results. By retrieving and analyzing literature, this study will demonstrate how AI can enhance the accuracy of diagnoses, tailor personalized treatment plans, and facilitate effective HF monitoring. Additionally, it will examine potential implications for future clinical practices and patient management in the context of HF, offering valuable insights into the future trajectory of integrating AI with HF; and assisting researchers in the HF discipline to adopt these systematic research trends.

Materials and Methods

Data Collection and Search Strategy

The articles were extracted from the commonly used databases for bibliometric analysis; Clarivate Analytics' Web of Science (WoS).[17,18] This collection mainly encompassed more than 21,800 highly ranked academic journals and more than 200,000 conference proceedings from around the globe. It includes various disciplines such as natural sciences, engineering technology, biomedicine, social sciences, and the arts and humanities with data published from 1900. The bibliometric indicators of the research included the title, author information, institution, country/region, and keywords. The Social Sciences Citation Index (SSCI) and Science Citation Index Expanded (SCI-expanded) were selected from the Web of Science Core Collection (WoSCC). To minimize bias from the daily data updates, the literature was restricted to January 1, 2004, to August 31, 2024. Three distinct researchers (MLC, LK and ZJY) executed the literature review to verify the reliability and legitimacy of the results. This analysis included original research and review articles. Published conference abstracts, papers in conference proceedings, and book chapters were excluded from this analysis.

The recommended keywords for artificial intelligence and heart failure (HF) were utilized based on previous studies[16] as follows: "Artificial intelligenc", "Machine learnin", "Heart failur", and "Heart decompensatio". The detailed search formula is as follows: TS= "Heart failur" OR "Cardiac failur" OR "Congestive Heart Failur" OR "Heart decompensatio" OR "Decompensation, Hear" OR "Chronic Heart Failur" OR "Acute Heart Failur" OR "Left Sided Heart Failur" OR "Right Sided Heart Failur") AND TS = "Artificial intelligenc" OR "Machine learnin" OR "Neural networ" OR "Deep learnin" OR "Computer visio" OR "Big dat" OR "Machine Intelligenc") AND LA= (English) AND DT = (Article OR Review). A total of 799 articles were included after the initial search and screening. However, 115 articles with missing keywords were excluded from this review, and 684 articles were retained for analysis. The articles ultimately selected from the WoSCC database were exported as "Full Record and Cited Reference" in the "Plain text fil", and the TXT file was retained for subsequent data analysis. Further details of the inclusion and exclusion criteria of the literature are illustrated in Figure 1.

Data Visualization and Analysis

Visual analysis was performed using Microsoft Office Excel 2016, Citespace 6.4.R1,[19] VOSviewer 1.6.20,[20] SCImago Graphica 1.0.45, and Pajek 5.19. VOSviewer is a tool utilized to analyze, visualize, and comprehend various types of information such as academic literature, knowledge networks, collaborative relationships, and emerging research trends. To determine the co-occurrence patterns of countries and journals VOSviewer in conjunction with Pajek was utilized to conduct co-occurrence analysis. Nodes with similar colors indicated the same clusters and the node's size reflected its frequency. SCImago Graphica was utilized to illustrate collaborations among countries and to generate annual statistical charts of national publications. Citespace has various functions such as co-occurrence, clustering, and emergence analysis; it also has analytical tools such as path analysis, cluster analysis, and timeline analysis, which generate pertinent visual maps for institutions, keywords, and co-cited documents, thereby providing the researchers with deeper

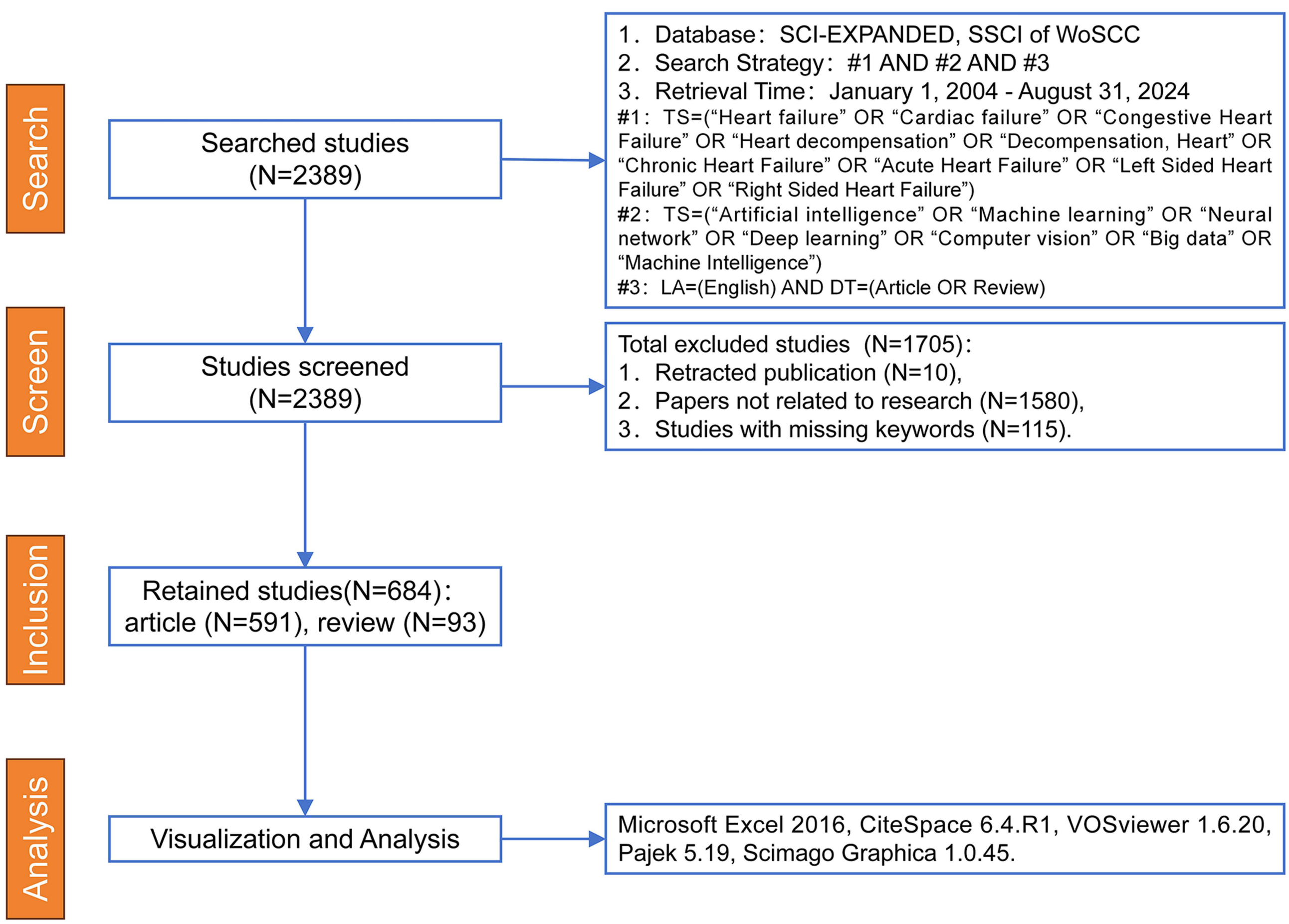

Figure 1 Literature screening flowchart.

insight into the structure and development of academic disciplines.[19,21,22] The dimensions of the nodes indicate their regularity, the lines connecting the nodes represent their relationships, and the thickness of the lines indicates the magnitude of the associations between the nodes. The intensity number indicates how regularly the publications are cited. The red bar indicates the outbreak period in years. In enumerating the countries or regions of origin for the indexed documents, China included publications from Taiwan, Hong Kong, and Macau. British documents comprised publications from England, Northern Ireland, Scotland, and Wales.

Research Ethics

This analysis does not require ethical approval because it incorporates secondary literature from the common database.

Results

Analysis of the Trend of Annual Publications

Over the past 21 years, 684 articles on AI and HF have been collected from the WOS database according to the search criteria. The annual publication trend is illustrated in Figure 2. Based on image analysis, the publication trend is categorized into three phases: (i) The first initial stage spanned between 2004 and 2016 and exhibited a relatively low publication volume. The annual publication volume increased from 1 to 6 in that period, demonstrating average annual growth. This growth was gradual, resulting in a modest overall increase. (ii) The second stage spanned between 2017 and 2020 and exhibited a tremendous increase in the quantity of publications (from 13 publications in 2017 to 49 publications in 2020) with a 55.63% average annual growth. The publication volume in 2020 was 8.2 times more than that of 2016. The third stage ranged from 2021 to 2024 with the accelerated growth of the publication volume (from 95 publications in 2021 to 175 publications in 2024). The number of publications in 2024 has increased 3.6 times compared to 2020 and 29.2 times compared to 2016. To present the annual publication trend more intuitively, the exponential equation ($y = 1.0786e^{°.2836x}$ ($R^2 = 0.978$) was utilized where x denotes the years, and y denotes the annual publication volume (Figure 2). The curve trend displays predictive growth of the annual publication volume for the future. The annual HF publication volume is expected to reach 313 by 31st December 2024.

Analysis of Authors and Co-Cited Authors

Co-authorship cooperation network analysis revealed collaboration patterns and knowledge that are vast in the academic field and substantial comprehension of the social structure of scientific research promoting collaboration across disciplines. Additionally, 4610 authors collaborated to publish articles regarding AI and HF management (Supplementary Table 1). The data demonstrates that among the ten leading, highly prolific authors, Partho P. Sengupta and Sanjiv J Shah from the United States published the most articles (9 articles). Moreover, data denotes that most Chinese authors are mostly active in AI and HF

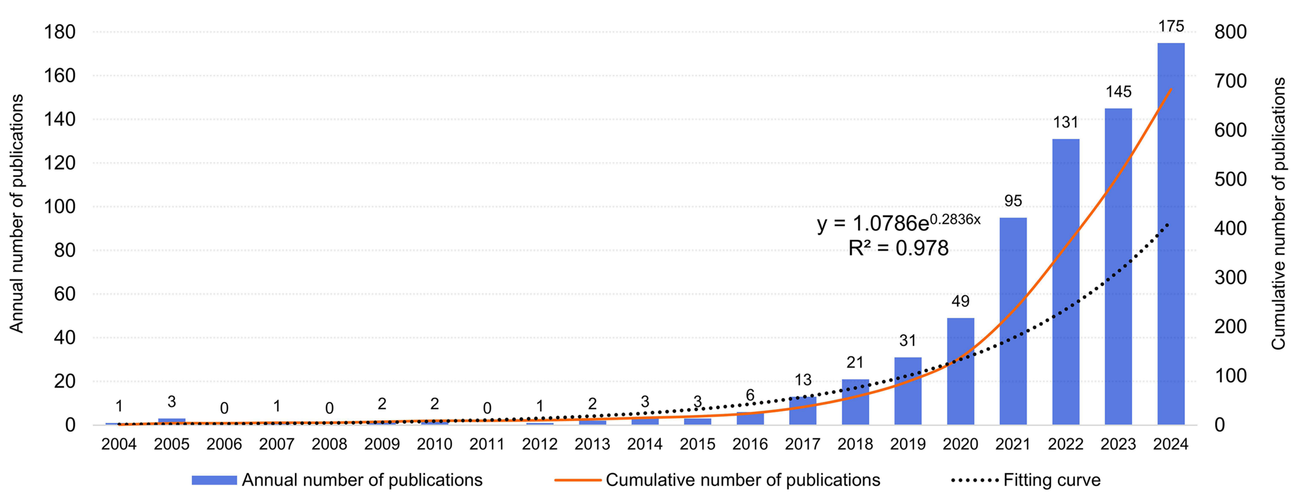

Figure 2 Global trends in research articles in heart failure discipline based on AI over the past 21 years.

management. Despite the low number of citations, there is varying intensity of the cooperation network indicating the presence of diverse models of academic exchange and cooperation.

Author co-citation analysis is a valuable technique that depicts academic influence, establishes networks of academic collaborations, identifies emerging research trends, and evaluates the scope and depth of research. The results reveal 17,421 cited authors; the ten leading authors had over 70 citations each. Shah, SJ (n = 168) had the most citations.

Analysis of Institutional and National Collaborations

Institutional analysis reveals the core strength of the academic field. Citespace was utilized to conduct visualization analysis for the institutions that have published the literature. A total of 303 nodes and 883 connections were obtained. Figure 3A displays the nodes with more than 5 publications and the information for the ten leading institutions illustrated in Supplementary Table 2. The data shows that Harvard University and the University of California System in the United States have the most publications (26 articles each). Additionally, Harvard University had the largest centrality (0.19) indicating a more prominent central position in AI and HF management.

National analysis can reveal research engagement and the global impact of various regions in the domains of AI and HF. Seventy countries participated in AI and HF research. Supplementary Table 3 depicts the 10 leading countries in terms of publication quantity. The United States reveals the greatest publications quantity (228 articles) followed by China (192 articles). The quantity of publications in these countries is significantly higher. Regarding the Total link Strength (TLS), the TLS value increased with the increasing connections across the nodes. The UK has the highest TLS value (175), subsequent by the United States (172) denoting that a higher number of co-occurrences may have an elevated frequency of research collaborations and exchanges. The United States is also far ahead in terms of citations, centrality, and H-index, indicating its substantial volume of high-quality research in this field, highlighting that it holds a leading position in global scientific research output. The annual publication volume of countries displayed in Figure 3B depicts that the United States resumed significant literature publications from 2005 and published additional articles in

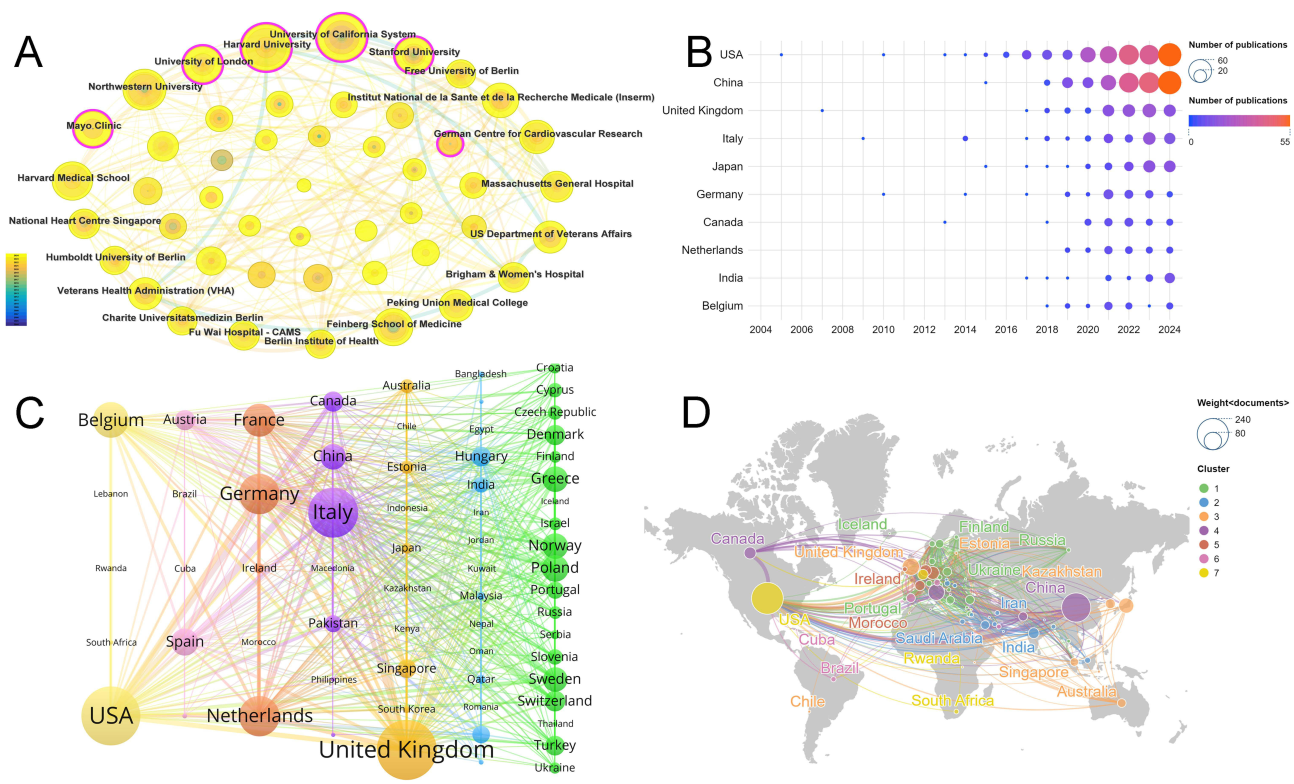

Figure 3 Visualization of institutions and countries/regions from 2004–2024. (**A**) A visual representation of the institutions. The node size indicates the number of posts. (**B**) The annual publication volume of the top ten countries/regions in total publication volume. (**C**) Node size by country based on TLS settings. (**D**) A map illustrating the collaborations between the countries. The lines represent the collaborations between countries and the thickness of those lines indicates the intensity of the collaborations.

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the past five years. China's annual publication volume has been escalating every year since 2018. VOSviewer was utilized to visualize the 70 countries that published the literature, and the 4 isolated nodes were eliminated. The association strength in the software normalization was used for clustering, and 7 clusters were obtained. The node size was set according to TLS (Figure 3C). The associations between countries are shown in Figure 3D.

Analysis of Journals

A total of 684 articles regarding AI in HF were published in 272 journals citing 5961 journals since 2004 (Supplementary Table 4). These journals demonstrated that most articles (40) were published in Frontiers in Cardiovascular Medicine. The Impact Factor (IF) and Journal Citation Report (JCR) of journals reveal the academic influence and recognition of the journals. The data demonstrates that most journals were from the first quartiles (Q1) or second quartiles (Q2), highlighting a substantial significance and influence in their respective fields. The minimum quantity of documents of a source in VOSviewer was set to 5 and 35 nodes were obtained (Figure 4A). The node size represents the number of publications and the color represents the IF of the journal.

The citation frequency of a co-cited journal reflected the journal's influence on research and indicated the recognition and the general impact of its published research articles in a particular field. The ten leading co-cited journals are illustrated in Supplementary Table 4; Circulation depicts the highest co-citation frequency (1596). These ten journals are all Q1 or Q2 journals; Setting the minimum number of citations of a source in VOSviewer to 100, 44 nodes were obtained (Figure 4B). The node size represents the citation frequency and the color represents the IF value of the journal.

The dual graph overlay function of Citespace assists in constructing the main distribution of academic journals. The fundamental aspect lies in the connection between the citing and the cited domain. The overlay graph illustrates the flow of knowledge across disciplines at the journal level (Figure 4C). The left section represents the citing graph, and the right section illustrates the citation graph. The curve depicted is the citation line, which comprehensively demonstrates the origin and evolution of the citation. This figure shows two main citation routes: 1) medicine, medical, clinical-health, nursing, medicine (z = 7.25, f = 2675), and 2) medicine, medical, clinical-molecular, biology, genetics (z = 3.35, f = 1294).

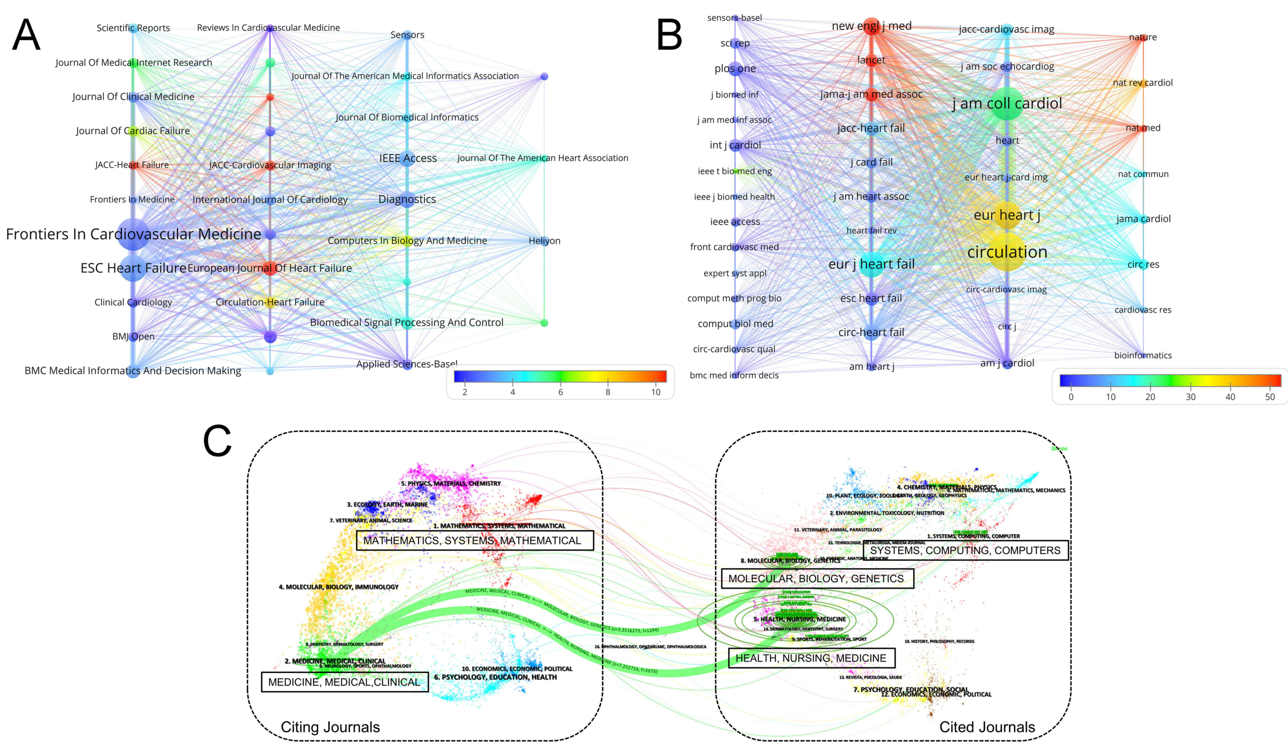
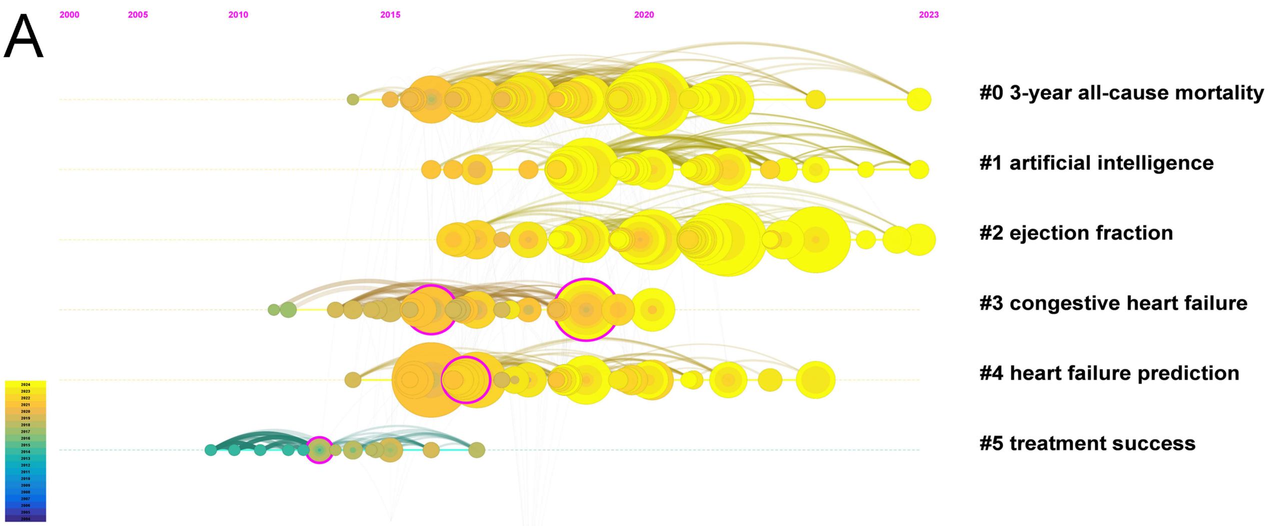


Figure 4 Visualization of journals and co-citation journals from 2004–2024. (**A**) Network map of published journals. (**B**) Network map of cited journals. (**C**) Dual-image overlay in the field of AI and HF.

Analysis of Co-Citations

The co-citation relationship among documents is subject to change in the coming years. Analyzing the co-citation network of documents provides insights into the advancement and evolution of AI and HF research. The ten leading co-citations are illustrated in Supplementary Table 5. The most cited references are the European Society of Cardiology (ESC) protocols diagnosing and treatment in acute heart failure (AHF) and chronic heart failure (CHF), which were published by Piotr Ponikowski et al in 2016 and comprised 46 citations. The co-citations were clustered utilizing the log-likelihood ratio (LLR). The results demonstrated Q = 0.7906 and S = 0.9012, indicating a strong, credible network clustering effect. Figure 5A illustrates how key research areas evolved over the years utilizing the timeline view of the co-citations. The six largest clusters were selected for analysis to comprehend the development trend. The latest research hotspots are the "3-year all-cause mortality" (#0), "artificial intelligence" (#1), "ejection fraction" (#2), and "heart failure prediction" (#4). This denotes that in the HF discipline, researchers employ AI techniques to analyze the key indicators including ejection fraction to predict the precise incidence of HF, consequently optimizing the therapeutic approaches and improving patient prognosis. Figure 5B demonstrates the 26 leading references with the most significant citation surge.

A



B

Top 26 References with the Strongest Citation Bursts

References	Year	Strength	Begin	End	2004 - 2024
Shah SJ, 2015, CIRCULATION, V131, P269, DOI 10.1161/CIRCULATIONAHA.114.010637, DOI	2015	12.33	**2017**	2020	
Masetic Z, 2016, COMPUT METH PROG BIO, V130, P54, DOI 10.1016/j.cmpb.2016.03.020, DOI	2016	6.81	**2017**	2021	
Liu GZ, 2014, PLOS ONE, V9, P0, DOI 10.1371/journal.pone.0093399, DOI	2014	4.07	**2017**	2019	
Deo RC, 2015, CIRCULATION, V132, P1920, DOI 10.1161/CIRCULATIONAHA.115.001593, DOI	2015	3.49	**2017**	2019	
Shahbazi F, 2015, COMPUT METH PROG BIO, V122, P191, DOI 10.1016/j.cmpb.2015.08.007, DOI	2015	3.49	**2017**	2019	
Narin A, 2014, COMPUT BIOL MED, V45, P72, DOI 10.1016/j.compbiomed.2013.11.016, DOI	2014	3.49	**2017**	2019	
Yancy CW, 2013, J AM COLL CARDIOL, V62, PE147, DOI 10.1016/j.jacc.2013.05.019, DOI	2013	3.21	**2017**	2018	
Ponikowski P, 2016, EUR HEART J, V37, P2129, DOI 10.1093/eurheartj/ehw128, DOI	2016	17.83	**2018**	2021	
Mortazavi BJ, 2016, CIRC-CARDIOVASC QUAL, V9, P629, DOI 10.1161/CIRCOUTCOMES.116.003039, DOI	2016	7.26	**2018**	2021	
Tripoliti EE, 2017, COMPUT STRUCT BIOTEC, V15, P26, DOI 10.1016/j.csbj.2016.11.001, DOI	2017	5.23	**2018**	2020	
Benjamin EJ, 2017, CIRCULATION, V135, PE146, DOI 10.1161/CIR.0000000000000485, DOI	2017	4.26	**2018**	2020	
Choi E, 2017, J AM MED INFORM ASSN, V24, P361, DOI 10.1093/jamia/ocw112, DOI	2017	3.46	**2018**	2020	
Savarese Gianluigi, 2017, CARD FAIL REV, V3, P7, DOI 10.15420/cfr.2016:25:2, DOI	2017	4.97	**2019**	2022	
Chen WH, 2016, PLOS ONE, V11, P0, DOI 10.1371/journal.pone.0165304, DOI	2016	3.68	**2019**	2021	
Chen TQ, 2016, KDD16: PROCEEDI ...... ERY AND DATA MINING, V0, PP785, DOI	2016	5.18	**2020**	2021	
Ahmad T, 2018, J AM HEART ASSOC, V7, P0, DOI 10.1161/JAHA.117.008081, DOI	2018	4.85	**2020**	2021	
Nagueh SF, 2016, J AM SOC ECHOCARDIOG, V29, P277, DOI 10.1016/j.echo.2016.01.011, DOI	2016	3.76	**2020**	2021	
Sanchez-Martinez S, 2018, CIRC-CARDIOVASC IMAG, V11, P0, DOI 10.1161/CIRCIMAGING.117.007138, DOI	2018	3.63	**2020**	2022	
Yancy CW, 2017, CIRCULATION, V136, PE137, DOI 10.1161/CIR.0000000000000509, DOI	2017	3.37	**2020**	2022	
Desai RJ, 2019, JAMA NETW OPEN, V2, P0, DOI 10.1001/jamanetworkopen.2019.18962, DOI	2019	3.11	**2020**	2022	
Virani SS, 2020, CIRCULATION, V141, PE139, DOI 10.1161/CIR.0000000000000757, DOI	2020	4.31	**2021**	2022	
Hedman ÅK, 2020, HEART, V106, P342, DOI 10.1136/heartjnl-2019-315481, DOI	2020	4.19	**2021**	2022	
Frizzell JD, 2017, JAMA CARDIOL, V2, P204, DOI 10.1001/jamacardio.2016.3956, DOI	2017	3.52	**2021**	2022	
Ambale-Venkatesh B, 2017, CIRC RES, V121, P1092, DOI 10.1161/CIRCRESAHA.117.311312, DOI	2017	3.31	**2021**	2022	
Kwon JM, 2019, PLOS ONE, V14, P0, DOI 10.1371/journal.pone.0219302, DOI	2019	3.31	**2021**	2022	
Zhang J, 2018, CIRCULATION, V138, P1623, DOI 10.1161/CIRCULATIONAHA.118.034338, DOI	2018	3.37	**2022**	2024	

Figure 5 Visualization of co-cited references from 2004 to 2024. (**A**) Co-citation reference timeline view. (**B**) The top 26 most cited references in AI-based HF research.

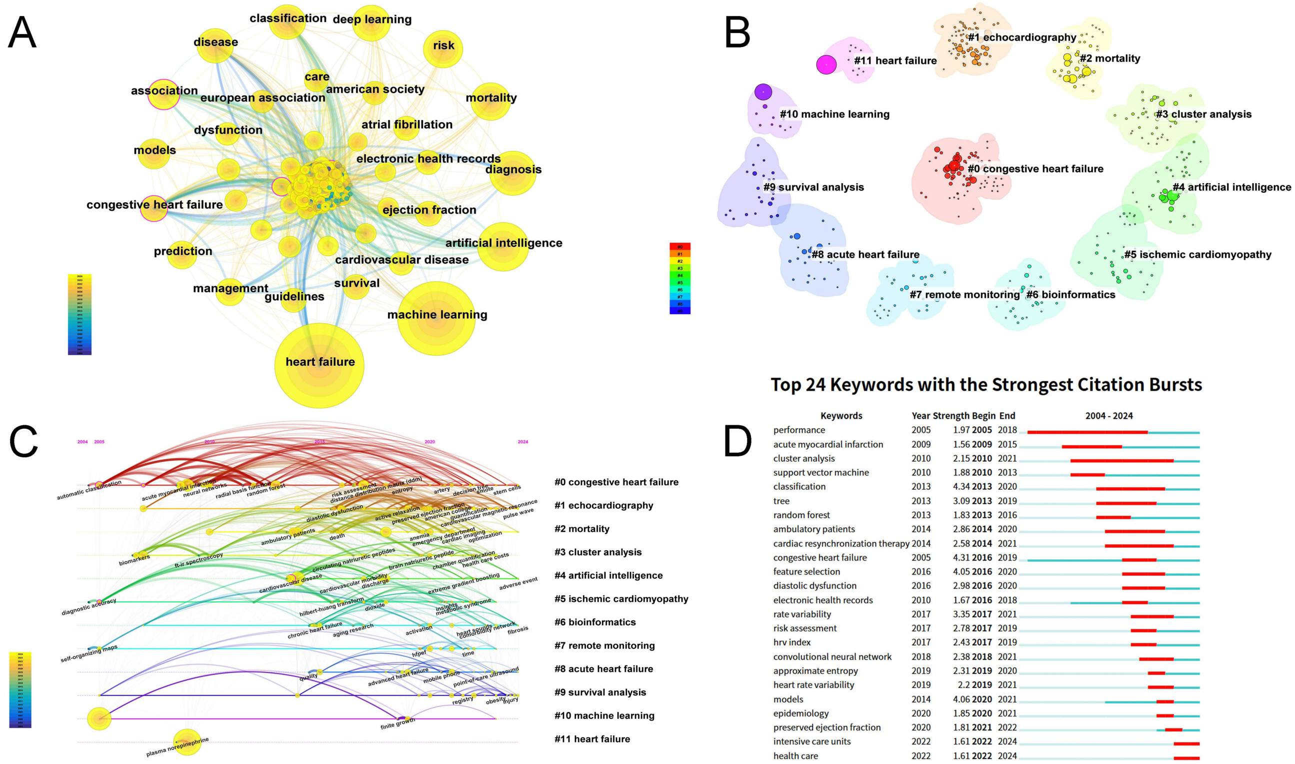


Figure 6 Visualization of keywords from 2004 to 2024. (**A**) The network of keywords. (**B**) keyword clustering. (**C**) Keyword Timeline View. (**D**) The top 24 keywords with the strongest citation burst.

Analysis of Keyword Networks

Keywords are primarily the foundation of an article. Analyzing keyword co-occurrence portrays significant research areas and fundamental concerns, illustrating the correlations between keywords and the evolution of research topics, thereby assisting researchers in comprehending the dynamics within the field. Citespace was utilized to draw keyword visualization maps (Figure 6A). The 20 leading keywords are presented in Supplementary Table 6. High-frequency keywords include "heart failure", "machine learning", "artificial intelligence", and "diagnosis". In Citespace software, keywords with centrality ≥0.1 present high significance, and influence the network. The centrality measure of "congestive heart failure" is 0.13, while the "heart failure" and "association" have a centrality of 0.1, indicating that they have a supportive function within the network.

LLR cluster analysis was performed on the keywords and 12 clusters were identified (Figure 6B). This included Q = 0.4745 and S = 0.7517, indicating a significant clustering effect, with clusters exhibiting strong internal cohesion and being with substantial differences. The largest cluster identified is Cluster #0, which pertains to congestive HF. To further investigate the keywords related to the application of AI in HF discipline, the timeline view analysis was employed (Figure 6C). By analyzing the growth rate of each cluster over time, we can comprehensively investigate fundamental research questions in this domain from a micro perspective.

Figure 6D illustrates the 24 leading keywords that exhibited the most significant emergence. The keyword with the highest burst intensity is "classification" (4.34), which first appeared in 2013 and proceeded until 2020. The term "Performance" emerged early in (2005) and maintained its presence for the longest duration, with its relevance declining by 2018. The "Intensive care units" and "health care" emerged in 2022.

Discussion

At present, bibliometric methods are frequently utilized to identify the latest developmental trajectories in a particular research discipline. Currently, there are limited bibliometric analysis studies integrating AI and HF if any at all.

Therefore, this study intends to investigate the novel trends regarding the potential impact of AI on HF and to provide an innovative perspective for subsequent research.

General Information

The analysis of data and visualization software derived from the WOS database was employed to systematically review the published literature regarding AI in HF research for the past 2 decades (2004 to 2024). In the discipline of AI in HF, there has been a significant increase in annual publication output, particularly in the past 4 years (2021–2024). During this period, a total of 546 articles were published, accounting for 80% of the total publications count. Although the data on the articles published in 2024 is only available up to August 31, the annual number of articles published has reached the highest level in the past two decades. Projections based on the fitted curve suggest that the number of published articles will constantly escalate from 2024 to the later years. This trend indicates a growing interest among researchers in utilizing AI within the HF discipline, leading to more vigorous research initiatives. It is imperative to anticipate the emergence of progressive advancements and innovations in this department.

The analysis of publication volume and co-cited authors provide significant insights for bibliometric analysis initiating the discovery of highly influential scholars elucidating academic collaboration networks and informing research trajectories. Regarding the author information, Sengupta, Partho P. Shah, and Sanjiv J from the United States have published 9 articles ranking at the forefront of publications. Sengupta, Partho P's research primarily centers on echocardiographic imaging of HF, analysis of myocardial mechanics analysis, and application of machine learning techniques in evaluating cardiac function.[23–25] His work merges traditional imaging techniques with AI to enhance the accuracy of cardiac function assessment and tailored personalized therapies in HF patients. Conversely, Shah, Sanjiv J's research emphasizes precision medicine for HF with preserved ejection fraction, concentrating on the identification and classification of patients through techniques such as phenotype mapping, deep phenotyping, machine learning, and designing innovative clinical trials to optimize individualized treatment strategies.[26–28] Citation metrics indicate that Shah, Sanjiv J hold the highest citation count among the authors. This data underscores these authors' significant contributions and prominent roles in the discipline.

The analysis of national and institutional publications provides significant insights and assistance for bibliometrics, particularly in evaluating the strength of scientific research, revealing collaborative networks, directing resource allocation, and comprehending research features. According to the results of national analysis, the United States and China rank as the leading countries in publication volume within this domain. However, China's citation frequency and H-index remain lower than that of the United States. Its TLS value and centrality are also relatively low. Therefore, China should improve the quality of research articles, engage proactively in international scientific research collaborations, advance academic research, and strengthen its international collaborations and academic impact in this domain in the coming years. The institutions that generated the highest publication count are Harvard University and the University of California system in the United States. This highlights the substantial advantages of the United States regarding academic resources, interdisciplinary collaboration, and scientific research quality. Furthermore, the study also indicates that although China has an elevated publication count, there is no institution among the first 10 rankings, implying that its research initiatives are relatively scattered and predominantly conducted independently across multiple institutions. It is recommended that relevant departments provide additional support to key research institutions, promote integration of resources, and facilitate collaborative innovation to enhance international competitiveness and influence in this domain.

Investigations of journal publication volumes and co-cited journals are crucial for identifying key journals, comprehending knowledge dissemination, revealing research frontiers and directing resource allocation. The results indicate that Frontiers in Cardiovascular Medicine and ESC Heart Failure are pivotal journals in this domain, with a high publication count and significant academic influence. In addition, the co-cited journals: Circulation and Journal of the American College of Cardiology are the foundational references in the field, highlighting the concentration of prominent research results within these journals. The publication status of the interdisciplinary journal IEEE Access reveals the importance of interdisciplinary collaborations in AI and cardiovascular research.

Research Hotspots

This study identified research hotspots of AI in the HF discipline from the co-occurrence investigations of cited literature and keywords. These hotspots were divided into three major aspects: AI-driven diagnosis and predictive risk of HF, exploration of HF mechanisms, and AI-based personalized management such as remote monitoring and multi-omics data fusion.

Artificial Intelligence-Driven Heart Failure Classification Diagnosis and Risk Prediction

HF represents a global cardiovascular disease with intricate conditions and diverse classifications.[29] Traditional diagnostic methods such as echocardiography and electrocardiogram (ECG) are essential tools for evaluating CVDs, and the associated indicators are often utilized in the diagnosis of HF.[30,31] However, hurdles such as potential diagnostic errors by doctors and insufficient allocation of medical resources often hinder the timely diagnosis of HF, particularly in the analysis of diagnostic data. Consequently, there is a pressing necessity to establish an automated ECG diagnostic system with high efficacy that incorporates machine learning technology to facilitate precise classification of heart diseases.

HF diagnosis is classified into AHF and CHF according to the severity of disease onset. The research of Youngjin Cho et al developed an AI-based electrocardiogram (ECG) analysis algorithm called quantitative electrocardiogram (QCG). The study verified the effectiveness of QCG in predicting the risk of cardiac death during hospitalization and in the long term through the data of AHF patients in the hospital, indicating that the QCG score may become a new marker for assessing the risk of HF patients.[32] Yineng Zheng et al developed a computer-aided diagnosis system for chronic heart failure, which achieved high-precision detection of CHF by extracting the cardiac reserve index and the characteristics of heart sound integrated with an AI diagnosis model.[33]

Based on the ejection fraction, HF can be divided into heart failure with preserved ejection fraction (HFpEF), heart failure with reduced ejection fraction (HFrEF), heart failure with intermediate ejection fraction (HFmrEF), and heart failure with improved ejection fraction (HFimpEF), with the first three types of HF being mostly studied. Matthew W Segar used unsupervised cluster analysis in machine learning to identify three phenotypic subgroups exhibiting varying clinical traits and long-term outcomes in the cardiac HFpEF patient population and revealed that patients in phenotypic subgroup 1 were at high risk of adverse outcomes.[34] This study substantiated the efficacy of machine learning cluster analysis in identifying phenotypes of HFpEF patients characterized by distinct clinical traits and long-term outcomes. Mon Myat Oo et al used deep learning algorithms to combine electronic health record data and echocardiographic images to attain automated detection and accurate classification diagnosis of HFrEF patients.[35] The study has effectively identified HFrEF patients by automatically interpreting echocardiographic images, extracting the key functions of cardiac parameters by combining clinical information and revealing significant differences in their characteristics and echocardiographic parameters. Marta Afonso Nogueira et al used knowledge-enhanced neural networks to process electrocardiograms and novel biosignals (phonocardiograms and mechanical force biosignals) to identify structural and functional cardiac abnormalities associated with HFmrEF.[36]

HF patients have a considerable risk of mortality and readmission, substantially straining the patients and the healthcare system.[37] In this context, the application of predictive models is crucial. Muhammad Shahzeb Khan believes that AI risk prediction models have stronger predictive capabilities relative to traditional methods, and they can potentially solve the key challenges in HF management, such as optimizing treatment allocation for high-risk patients, predicting adverse outcomes, and detecting early subclinical or worsening cases, thereby playing a vital role in HF care.[38] Suveen Angraal employed five distinct machine learning methods to build a model aimed at predicting the risk of hospitalization and death attributed to HF in HFpEF patients, validating the model's efficacy through cross-validation.[39] Valeria Visco developed an innovative diagnostic model grounded in genetic programming to forecast the progression of HF, coupled with an easily interpretable 3D graphical representation.[40] By validating clinical data, this model can facilitate rapid diagnosis and targeted treatment of HF to reduce hospitalization rates.

The use of AI in HF has significantly advanced the diagnosis, classification, and prediction risk of HF. Integrating larger datasets and more precise AI algorithms will enhance the management of HF, potentially leading to improved accuracy in diagnosis and risk management.

AI-Based Personalized Management and Remote Monitoring

HF is frequently characterized by unstable phases throughout its progression. Even with diligent in-person monitoring, the incidence of adverse events remains high. The implementation of remote monitoring may improve clinical outcomes.[1] The advent of wearable and implantable cardiac devices introduced innovative cardiovascular diagnosis and treatment. These technologies facilitate the remote observation of disease progression by healthcare professionals, thereby creating opportunities for timely and effective interventions that may avert hospitalizations attributed to hemodynamic instability and adverse cardiac complications.[41] Nitesh Gautam noted that despite substantial advancements in diagnosing and treating HF leading to reduced mortality rate there has been a paradoxical rise in hospitalizations related to HF.[42] As data digitization expands progressively and accessibility improves, it is anticipated that remote monitoring through wearable and implantable devices will significantly transform outpatient workflow, particularly in minimizing hospitalization attributed to HF.

Remote dielectric sensing (ReDS) technology presents a quantitative and non-intrusive approach capable of measuring the total fluid volume in the lungs. Pulmonary congestion is a leading cause of hospitalization for exacerbated HF, influencing remote monitoring to impact optimal treatment positively to minimize the likelihood of re-hospitalization. Research conducted by Offer Amir et al indicated that ReDS-guided management could significantly lower the re-hospitalization rates among patients recently discharged following decompensated HF.[43] The LINK-HF research multi-sensor non-intrusive remote monitoring to predict exacerbated HF can aim to assess the efficacy of a personalized analytical platform that utilizes continuous data streams to forecast re-hospitalization following HF admission. Additionally, Josef Stehlik invented a prognostic algorithm employing machine learning techniques to identify HF exacerbations utilizing a disposable multi-sensor patch worn on the chest to record physiological data continuously for 3 months.[44] The research ultimately demonstrated that multivariate physiological telemetry from wearable sensors can accurately detect the risk of impending rehospitalization at an early stage. Numerous wearable devices are utilized externally and consistently to collect functional or physiological data enhancing patients' heart health.[45,46] The authors discovered that wearable devices have substantial potential in remote detection of HF, the existing data are primarily restricted to observational studies and small randomized controlled trials. This limitation hinders the HF medical community from accumulating extensive real-world efficacy data. Therefore, high-quality detection models should be promoted; the infrastructure should be invested; and multidisciplinary collaborations should be performed to facilitate system alterations to enhance the application of innovative technologies.

Multi-Omics Data Fusion and Exploration of Heart Failure Mechanisms

As a complex disease, the development and advancement of HF are affected by the comprehensive influence of multiple omics levels, including the genome, transcriptome, and proteome. Continuous advancement in AI, particularly in machine learning, bioinformatics, and big data analytics enabled researchers to integrate and analyze these diverse multi-omics datasets effectively. This integration enables the identification of critical features, thereby revealing the hidden pathological mechanisms behind HF and providing novel perspectives and strategies for the precise treatment of the disease. Wouter Ouwerkerk employed machine learning techniques and systems biology methods to integrate genetic, transcriptomic, and proteomic data in HF patients. Through this analysis, he discovered four major biological pathways significantly associated with all-cause mortality (MAPK; PI3K/Akt; Ras signaling; and epidermal growth factor receptor tyrosine kinase inhibitor resistance pathway). These pathways are associated with reduced modulation of the cardioprotective ERBB2 receptor and these findings were validated in an independent patient cohort, providing new potential targets for HF therapy.[47] Moreover, Jing Wu et al integrated recent multi-omics data and knowledge from diverse public sources to invent the Heart Failure Integrated Platform (HFIP) for HF.[48] This platform provides data exploration, the functions of fusion analysis and visualization including extensive datasets, analytical processes, and independent tools. Additionally, acknowledgment based on HF and literature retrieval modules was established to provide comprehensive support for basic and clinical research in the HF discipline. Through research regarding the molecular pathways of HF, Xiwei Deng analyzed gene expression data related to HF bioinformatics methods. He identified 15 differentially expressed autophagy-related genes and identified TPCN1, MAP2K1, S100A9, and CD38 through functional enrichment analysis and machine learning screening.[49] Vijayakrishna Kolur utilized bioinformatics analysis to thoroughly explore candidate indicators and treatment agents for HF.[50] The researchers employed high-throughput sequencing data and bioinformatics tools to screen 881 differentially expressed genes from multiple samples. This analysis identified the primary genes including TK1, PPP2R2B, LCK, PYHIN1, PCLAF, TP63, ESR1, ECT2, CFTR, and FKBP5. Through various analytical methodologies such as gene ontology enrichment, protein–protein interaction network construction, and module analysis. These chromosomes are related to the advancement of HF and may function as prognostic and diagnostic biomarkers and therapeutic targets. AI is essential in screening diagnostic indicators for HF and can examine the illnesses associated with HF. Chuanjing Zhang conducted a thorough bioinformatics analysis in combination with machine learning techniques to identify secretory proteins that connect major depressive disorder (MDD) with HF, highlighting essential genes and developing a diagnostic nomogram. Concurrently, animal studies verified the inverse correlation between these key genes and cardiac function.[51] In summary, by integrating multi-omics data and utilizing advanced machine learning techniques and bioinformatics methods, researchers can explore the underlying key features and molecular mechanisms of HF, providing novel targets and strategies for precise treatment. Concurrently, AI can assist researchers in comprehending the relationship between HF and related diseases. This will offer innovative strategies for disease diagnosis and treatment.

Future Trends

AI Helps Accurate Prediction of Heart Failure Management in ICU

Intensive care units (ICUs) are vital in treating HF, particularly patients with critical heart failure. Consistent monitoring and immediate interventions available in ICUs significantly mitigate the risk of complications and enhance patient survival rates.[52] AI advent technology has enabled the extraction of valuable insights from data. Recent research has utilized AI to forecast mortality and discharge outcomes for patients with HF ICUs. Zijun Chen et al developed a machine learning-based risk stratification tool employing the XGBoost algorithm to effectively evaluate the risk of in-hospital all-cause mortality among patients with congestive HF in the ICU.[53] The model outperformed the conventional risk prediction techniques, demonstrating superior discrimination and calibration in the external validation. Chih-Chou Chiu utilized the data from the MIMIC-III database to implement an enhanced stacking ensemble model that will precisely predict the mortality rate in HF patients in the ICU.[52] The model constructed an optimized stacking set of secondary classifiers by integrating the decisions of multiple primary classifiers achieving 95.25% accuracy and 82.55% AUROC. In predicting the discharge of ICU patients, Kaouter Karboub used the MIMIC III database to conduct multiple regression models to effectively allocate medical resources in the intensive care unit (ICU).[54] By evaluating the mean residual and processing time, the most effective model attained a 98% average accuracy and identified the area of the initial diagnosis and discharge, medicinal therapies, hospital stay, and internal referral are key factors affecting the patient's preparedness for the discharge. Additionally, Tadashi Kamio utilized a machine learning model technique to forecast clinical outcomes for patients with acute HF receiving furosemide treatment.[55] This indicates that AI effectively analyzes complex data and accurately predicts the treatment effect based on individual differences of patients, which assists with clinical decision-making, indicating the high expectations for AI to customize efficient personalized medical plans.

Resource Allocation and Optimization Under the Framework of Smart Healthcare

AI promotes efficient allocation and optimization of medical resources under the framework of smart healthcare. From the ICUs to community healthcare and telemedicine, AI has achieved precise management from diagnosis to the scheduling of resources through deep learning and machine learning technologies. Loucia Karatzia asserts that the primary aim of incorporating machine learning technology into HF research is the timely screening of high-risk patients; accurately classifying them according to their risk conditions; and implementing timely intervention strategies.[56] This will reduce the mortality rate by implementing early diagnosis and treatment. Therefore, hospitalization risks will be suppressed through these treatments and consistent follow-up in the community. In community and home healthcare, AI can perform early screening of high-risk patients and identify major issues such as significant differences in fairness indicators in various patient subgroups. Anahita Davoudi et al studied the fairness of machine learning models used to predict the risk of hospitalization and emergency department visits for HF patients receiving home care. By analyzing 12,189 home care data, they found that the performance of the model varied significantly among different demographic subgroups, emphasizing the importance of continuous monitoring and improvement of fairness indicators to mitigate bias.[57] Although AI has significantly improved the efficacy of medical resource allocation, in practical applications, ethical privacy protection, and model fairness issues should be considered to confirm the actual benefits of this technology for all patients.[58] Smart healthcare will further combine big data and AI technology to comprehensively improve the quality of patient care through precise allocation of resources and dynamic adjustment in the medical field.

Prediction of Heart Failure Progression Based on Multimodal Data

Prediction of HF progression based on multimodal data is a crucial trajectory of AI in HF management. This approach aims to achieve dynamic prediction of disease classification and progression by integrating multi-dimensional and multi-type patient data and providing a more reliable basis for precision medicine. Multimodal data includes electrocardiogram (ECG), medical imaging such as echocardiography and cardiac magnetic resonance, biomarkers including genome, proteome, metabolome and clinical data electronic health records, hospitalization records, and drug treatment.[59] Through the multimodal deep learning framework, AI technology can extract and fuse the key features of different modal data, extensively capture essential changes in disease progression, and provide risk prediction based on time series analysis. Through AI's clustering analysis and typing model, potential sub-phenotypes outside the existing classification system can be discovered, revealing the heterogeneity of the disease and facilitating individualized and stratified management.[60] In terms of progression prediction, time series analysis models (LSTM and Transformer) and traditional machine learning methods (XGBoost and random forests) can predict acute exacerbation and functional deterioration of the disease and optimize treatment timing and strategies.[30,61] Moreover, AI identifies the response of the patients to treatment plans through analysis of multimodal data, tailors treatment plans for high-risk patients, and provides a data basis for clinical decision support systems to promote real-time treatment adjustments and to improve the quality of life of the patients. However, the extensive application of this technology has some challenges regarding data standardization, model interpretability, privacy, and ethical issues. Future improvements in open-source data sets, algorithm optimization, multidisciplinary collaboration, and HF progression prediction based on multimodal data will lead to further development.

Limitations

This study used a bibliometric method to conduct a comprehensive analysis of the literature regarding the intersection of HF and AI in the Web of Science Core Collection (WoSCC) database to elucidate the current landscape of emerging trends and fundamental issues in this discipline. Although this study closely adhered to the standard protocols of bibliometric analysis, it has some limitations. First, the data source was primarily limited to WoSCC, potentially overlooking significant literature from other databases. Additionally, this study solely concentrated on the literature published in English, excluding significant materials available in other languages. Furthermore, this study included original research and review articles for the analysis, omitting other pertinent document types such as conference papers, book chapters, and communications. Finally, the research period was delineated from 2004 to 2024, which may have overlooked critical research findings from earlier years. Future studies can further broaden the literature search to reflect the research trends and advancements in the discipline. Nevertheless, this study provides a relative overview of the application of AI in the HF discipline.

Conclusion

Generally, this research systematically reviewed and analyzed the literature on the application of AI in HF discipline from the Web of Science database for the past two decades through bibliometric technique. It further revealed the emerging trajectories in the current and previous research and explored the major concerns in this discipline. This study revealed that, in the context of heart failure diagnosis, machine learning algorithms and deep learning models substantially enhanced diagnostic precision and risk prediction capabilities. When it comes to treatment and personalized management, AI technology facilitated remote monitoring and the development of tailored treatment strategies. In terms of mechanism exploration, the integration of multi-omics data and AI analysis uncovered potential biological pathways associated with heart failure. Furthermore, future research will likely center on ICU management, intelligent allocation of medical resources, and multimodal data prediction. Concurrently, it is imperative to prioritize the application of corresponding AI tools across various facets of heart failure management, while continuously exploring and optimizing them to foster advancements in this field. The United States and China are at the forefront of this research discipline. Countries and institutional researchers need to strengthen cross-regional and interdisciplinary collaboration to advance this field, ultimately benefiting most HF patients.

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Author Contributions

All authors made a significant contribution to the work reported, whether that is in the conception, study design, execution, acquisition of data, analysis and interpretation, or in all these areas; took part in drafting, revising or critically reviewing the article; gave final approval of the version to be published; have agreed on the journal to which the article has been submitted; and agree to be accountable for all aspects of the work.

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Disclosure

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