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Research article

Uncovering the scientific landscape: A bibliometric and Visualized Analysis of artificial intelligence in Traditional Chinese Medicine

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ABSTRACT

The emergence of artificial intelligence (AI) technology has presented new challenges and opportunities for Traditional Chinese Medicine (TCM), aiming to provide objective assessments and improve clinical effectiveness. However, there is a lack of comprehensive analyses on the research trajectory, key directions, current trends, and future perspectives in this field. This research aims to comprehensively update the progress of AI in TCM over the past 24 years, based on data from the Web of Science database covering January 1, 2000, to March 1, 2024. Using advanced analytical tools, we conducted detailed bibliometric and visual analyses. The results highlight China's predominant influence, contributing 54.35 % of the total publications and playing a key role in shaping research in this field. Significant productivity was observed at institutions such as the China Academy of Chinese Medical Sciences, Beijing University of Chinese Medicine, and Shanghai University of Traditional Chinese Medicine, with Wang Yu being the most prolific contributor. The journal *Molecules* contributed the most publications in this field. This study identified hepatocellular carcinoma, chemical and drug-induced liver injury, Papillon-Lefèvre disease, Parkinson's disease, and anorexia as the most significant disorders researched. This comprehensive bibliometric assessment benefits both seasoned researchers and newcomers, offering quick access to essential information and fostering the generation of innovative ideas in this field.

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1. Introduction

For thousands of years, Traditional Chinese Medicine (TCM) has integrated clinical practice with Chinese theories of disease prevention and treatment [1]. It is an ethnopharmacological system rich in natural resources and has accumulated significant experience in combating diseases, leaving a lasting impact on Chinese health [2–4]. Unlike modern medicine, TCM is grounded in ancient Chinese philosophies, employing dialectical treatment principles based on Yin-Yang, Wu-Xing, meridian, and Zang-Fu theories, viewing health holistically and systematically [5]. However, TCM's evolution has been hindered by the subjectivity of experience, ambiguity of language, and uncertainty of theory, as its progress and therapeutic approaches rely heavily on the accumulated knowledge and skills of experienced practitioners.

Since the early 1970s, artificial intelligence (AI) has been applied in medicine to enhance diagnostic and treatment efficacy [6]. As science and technology advance, AI's role in TCM is also expanding [7]. AI plays a crucial role in assessing TCM quality, identifying drug targets, optimizing compatibility, diagnosing conditions, and the emergence of "AI-TCM" pharmacy has gained significant academic attention [8–15]. Therefore, exploring AI applications in TCM and addressing the challenges of intelligent TCM analysis are essential for interdisciplinary research and advancing modern TCM in the AI era.

Although previous reviews have explored AI integration in TCM from various perspectives [1,2,7,11,16–18], they often lack empirical support from objective visual data, relying instead on subjective interpretations of the disciplinary framework. As a result, these evaluations show variability and subjectivity, hindering comprehensive analysis and the establishment of the current research landscape. Additionally, they pose challenges in identifying research focal points and cutting-edge directions. To overcome the identified limitations, this study utilizes a bibliometric analysis to visually represent the comprehensive landscape of the "AI-TCM" domain over the past 24 years (Fig. 1). Unlike conventional reviews, our study provides empirical evidence grounded in objective visual data, thereby minimizing subjective interpretation and reducing variability. This methodological approach allows for a more thorough analysis and aids in establishing the current research landscape. Furthermore, this study contributes to the existing literature by offering in-depth data analysis and visualization through advanced tools such as CiteSpace and VOSviewer.

This study addresses the following research questions (RQs): RQ1: What are the current trends in AI applications for TCM? RQ2: Which countries, institutions, and researchers hold the most influence in this field? RQ3: What are the key publications, references, and keywords? RQ4: What are the primary related diseases? The study integrates both quantitative and qualitative methodologies. Quantitative data encompass research themes, publication years, languages, journal scope, and detailed information on authors, countries, institutions, journals, and citations. The qualitative assessment emphasizes keyword mapping. Developing such a systematic and comprehensive knowledge base not only supports researchers from various fields in navigating this domain but also serves as a crucial reference for newcomers, guiding them toward promising research paths. To our knowledge, this study represents the first bibliometric analysis conducted on the "AI-TCM" field.

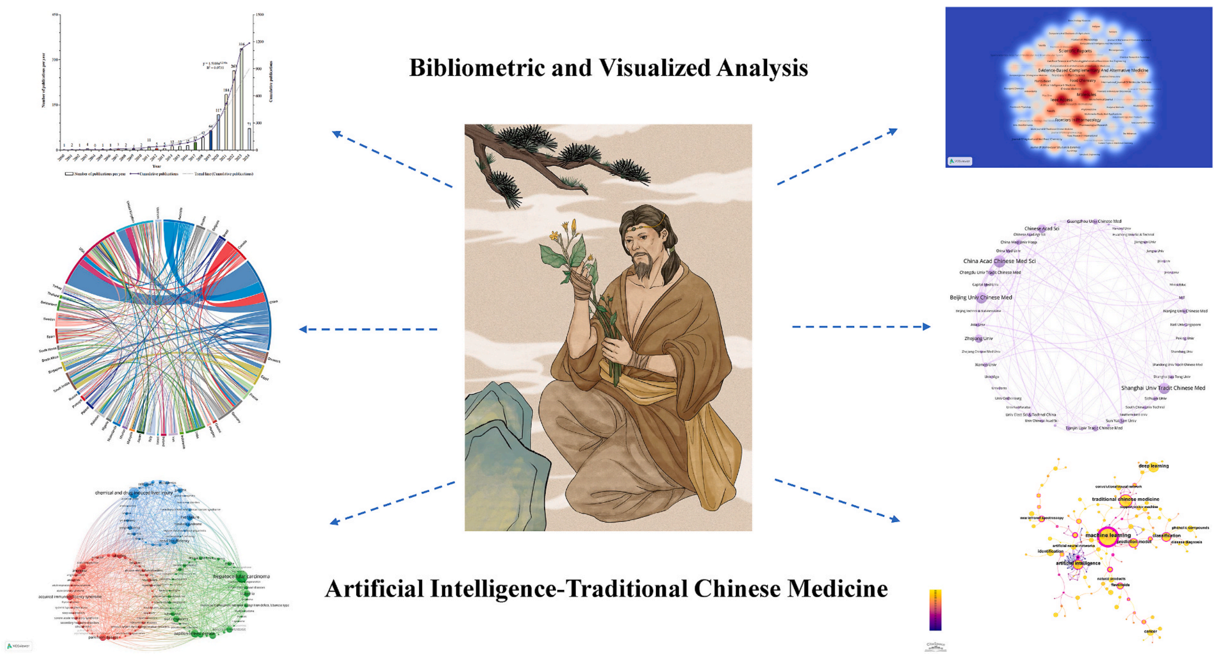


Fig. 1. A graphical abstract illustrating bibliometric and visualized analysis of artificial intelligence in Traditional Chinese Medicine. This figure was created using Figdraw (https://www.figdraw.com/static/index.html#/).

2. Materials & methods

2.1. Data source & retrieval strategy

The Web of Science Core Collection (WoSCC) allows researchers to monitor scientific frontiers, enabling comprehensive analysis and understanding of academic publication trends [19–22]. WoSCC serves as a key platform, offering bibliometric software for general statistics [21], and has shown superior accuracy in labeling document types compared to other databases [23]. In this study, a comprehensive online search using WoSCC was conducted to explore original research and reviews on AI applications in TCM. The search included articles published between January 1, 2000, and March 1, 2024, using a combination of Medical Subject Heading terms and keywords. The retrieval methodology underwent several revisions, guided by three researchers, aiming to enhance sensitivity and precision, as detailed in the Supplementary Materials.

2.2. Inclusion & exclusion criteria

Inclusion criteria encompassed investigations into the application of AI in TCM, including original research articles and reviews in

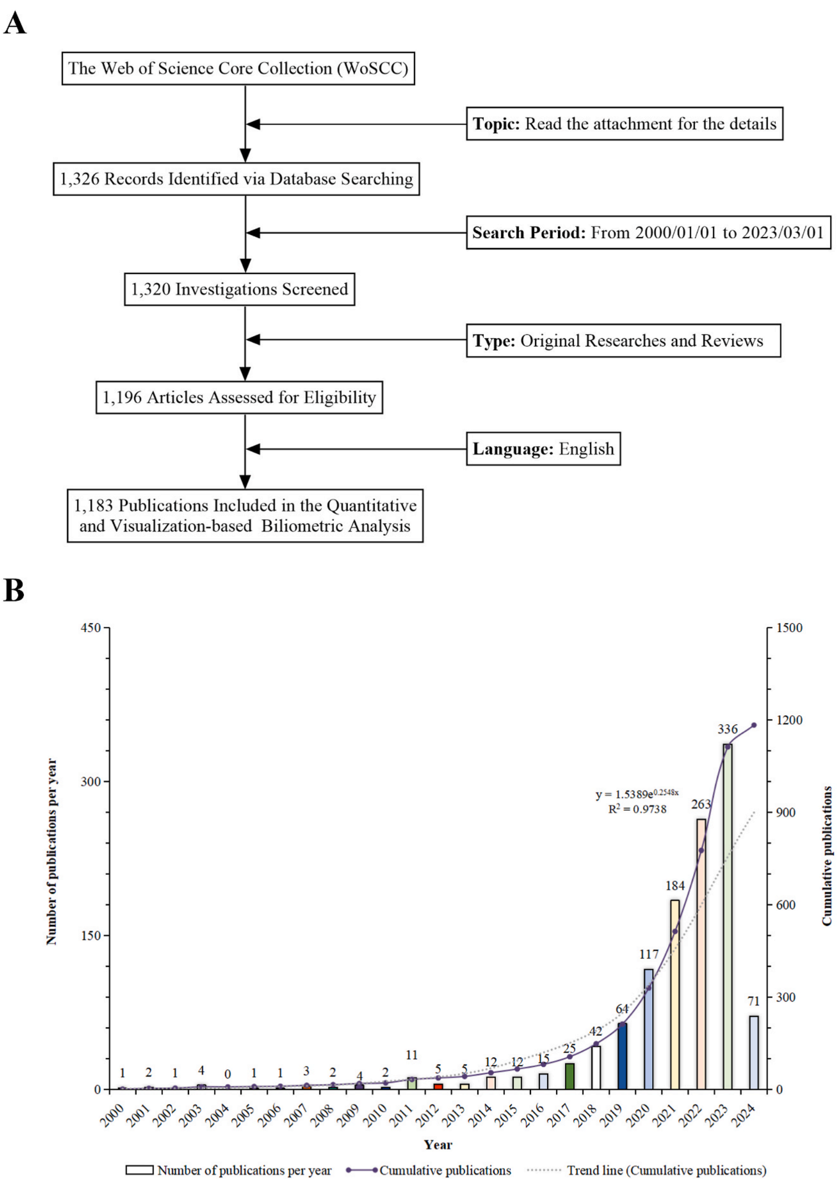


Fig. 2. (A) Schematic representation outlining the methodology employed for literature search and selection. (B) Temporal trend analysis depicting the evolution of research focused on "artificial intelligence-Traditional Chinese Medicine" from 2000 to 2024.

English-language publications. Exclusion criteria included dissertations, letters, commentaries, editorials, conference abstracts, and studies published under similar or different journal titles. The team members and peer groups extensively discussed the inclusion and exclusion criteria.

2.3. Bibliometric visualization & data analysis

Data from the WoSCC database was collected and imported into Microsoft Excel (Office 365, Microsoft). Following that, VOSviewer 1.6.18 (Leiden University, Netherlands), Citespace version 6.3.R1 (Chaomei Chen, China), Pajek version 5.16 (University of Ljubljana, Slovenia), Scimago Graphica version 1.0.35 (https://www.graphica.app/, USA), and the chorddiag R package (R Studio, version 4.2.0) were utilized for analysis.

To generate visual representations of national or regional collaborations and analyze published works, the chorddiag R package was used with VOSviewer. Co-occurrence and clustering analyses of countries/regions, institutions, authors, journals, research fields, and keywords were performed using VOSviewer, Scimago Graphica, and Pajek. Using Citespace, data on countries/regions, institutions, authors, journals, co-citations, and keywords were visually represented and analyzed. Additionally, the changing popularity of keywords over time was examined using Scimago Graphica.

Information about diseases was collected from the Citexs Data Analysis Platform (https://www.citexs.com). This tool simplifies the creation of visual charts, enabling thorough examination of the current state, key focuses, and future trends in this field.

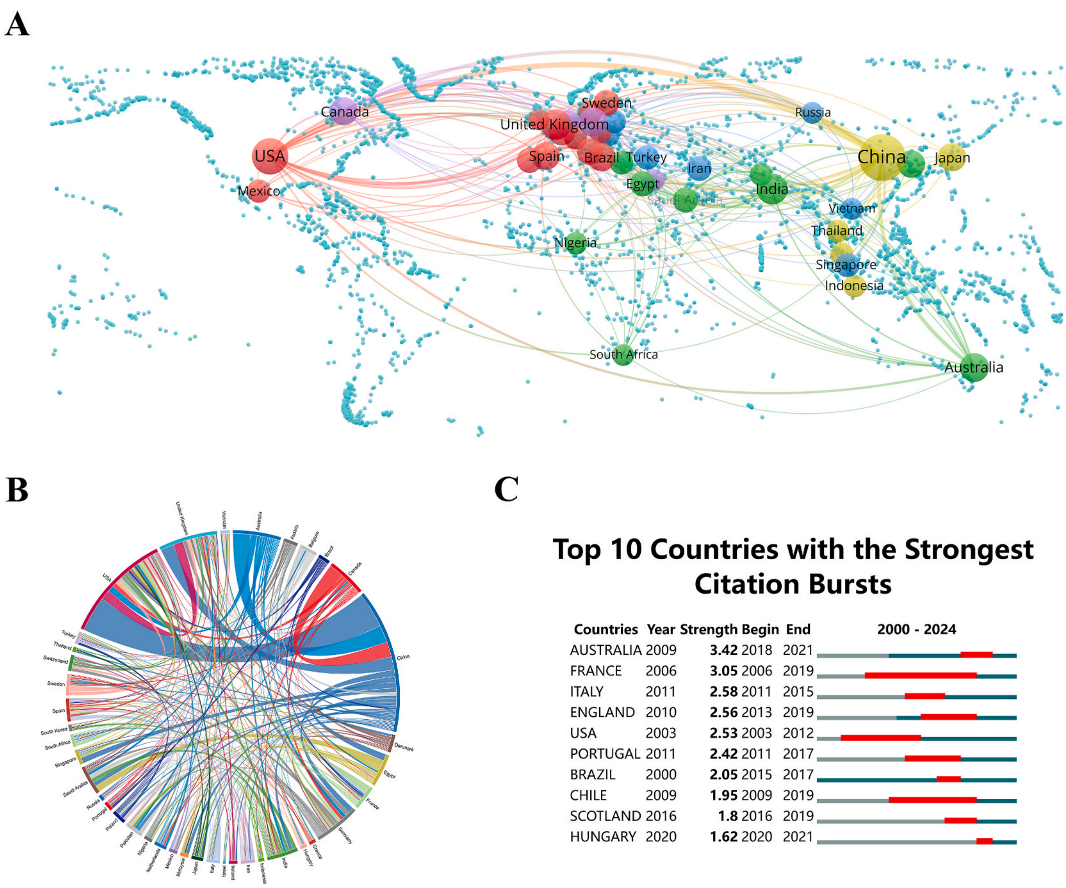


Fig. 3. (A) Global distribution of research on "artificial intelligence (AI)-Traditional Chinese Medicine (TCM)". Each sphere represents a country, with the thickness of connecting lines indicating the level of collaboration between nations. The size of each sphere corresponds to the number of publications from that country. (B) Chord diagrams illustrating international collaborations, where each outer curve represents a country, and the thickness of the lines denotes the strength of collaboration between countries. (C) Research output on "AI-TCM" from the top 10 countries (highlighted in red, indicating increased document production). "Burst" refers to a sudden increase in a research topic's prominence within a specific time period. BurstBegin marks the start of this phenomenon, signifying the onset of significant growth, while BurstEnd marks the conclusion, indicating when the growth trend slows or declines. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

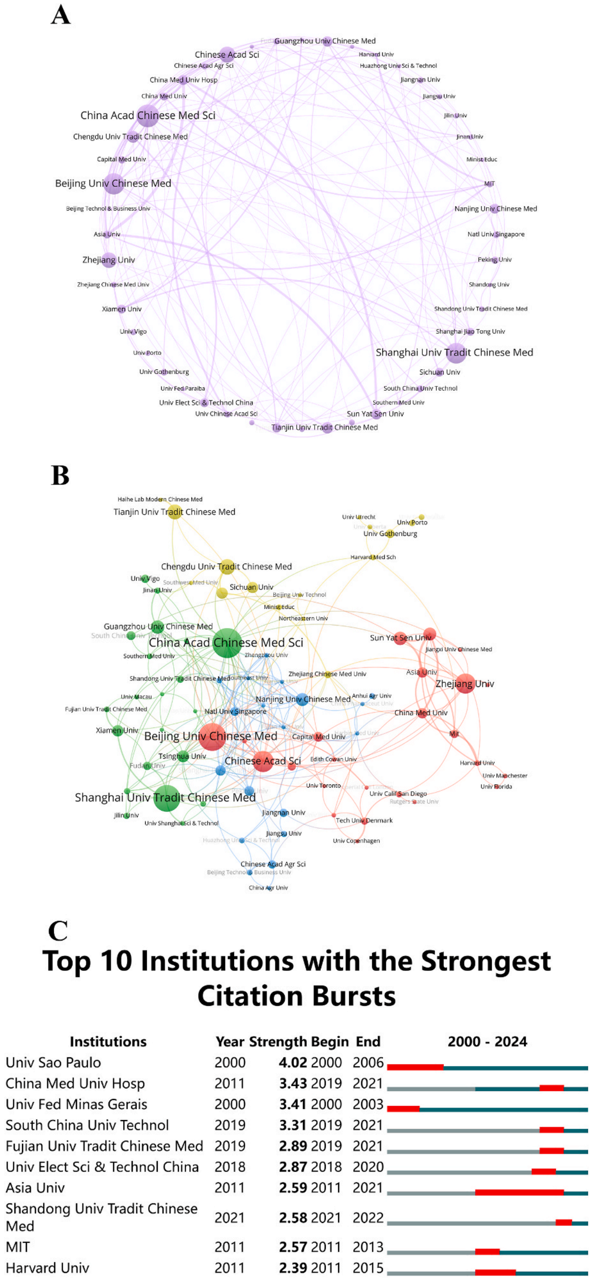


Fig. 4. (A) Institutional co-occurrence analysis map. The combination of spheres and text represents an entity, symbolizing an institution. Connecting lines between circles represent collaborative occurrences among institutions, with the thickness of the lines indicating the strength of collaboration between institutions. The size of circles is positively correlated with the number of publications from the institutions. (B) Clustering networks of research institutions, where distinct colors represent various clusters delineated by co-citation networks. Institutions with strong co-citation relationships are clustered, forming a hierarchical diagram. Line thickness between circles indicates the strength of cooperation, and circle size correlates with the number of documents published by each institution. (C) Citation bursts at the top 10 institutions (red bars represent periods of increased citation activity for institutions). "Burst" refers to a sudden increase in a research topic's prominence within a specific time period. BurstBegin marks the start of this phenomenon, signifying the onset of significant growth, while BurstEnd marks the conclusion, indicating when the growth trend slows or declines. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

3. Results & discussion

3.1. Scientific output

The data retrieval and collection method is shown in Fig. 2A. The progress of a study is often reflected by the number of scientific reports produced within a specified period [24,25]. From 2000 to 2024, 1,183 relevant scientific reports on "AI-TCM" were collected. This included 1,037 original articles and 146 reviews, with an average annual publication rate of 49.29. This underscores the significant attention and interest in this field. Starting in 2022, the annual number of relevant publications exceeded 200, peaking at 336 in 2023. The diagram shows a 67-fold increase since 2013, indicating a significant surge in research efforts and emphasizing the field's growing importance. The exponential equation ($y = 1.5389e^{0.2548x}$) captures the annual trend, with x representing the year and y the number of publications, showing a high R^2 value of 0.9738. This demonstrates the precision in data analysis, resulting in a well-fitting curve (Fig. 2B). The graph indicates a projected rise in annual research activities, reflecting growing interest in AI for TCM. Consequently, significant advancements are anticipated in this field in the coming years.

The academic value of the surge in "AI-TCM" research lies in its potential to bridge the gap between traditional medicine and modern technology. Applying AI to TCM preserves and modernizes an ancient medical system while contributing to the broader field of integrative medicine. Quantifying and analyzing TCM practices through AI provides new insights into their efficacy, potentially leading to the validation and refinement of TCM techniques within evidence-based medicine. As research output rises, it will likely attract more funding and collaboration, particularly between universities and biotech companies. This may lead to the commercialization of "AI-TCM" technologies, making them more accessible in clinical settings. Growing interest in "AI-TCM" is expected to attract expertise from various fields, including computer science, data analytics, and biomedical engineering, leading to interdisciplinary collaborations that could accelerate AI applications in TCM. Industry involvement could also drive the development of new products and services, potentially opening new markets for TCM. Increased research efforts might lead to more investments and partnerships between academia and industry in AI-driven TCM discoveries. The link between this research surge and the broader goals of modernizing and integrating TCM into healthcare underscores the field's potential to contribute significantly to global health.

3.2. Performance analysis

3.2.1. Countries/regions

Globally, research on "AI-TCM" spans 78 countries and regions. Fig. 3A and B depict national collaboration networks, illustrating the importance of each country or region in the domain, with a minimum of six publications from each. This provides valuable insights for strategic collaborations and knowledge exchange [26]. Notably, China leads with 643 publications, accounting for 54.35 % of total research output, highlighting its crucial role in advancing knowledge in "AI-TCM". The Chinese government's policies have prioritized AI as a critical technology for national development, with significant investments in AI research and infrastructure. This has led to the establishment of numerous research institutions and partnerships dedicated to exploring AI applications in various fields, including TCM. The USA and India also make significant contributions, accounting for 13.52 % (160 publications) and 5.07 % (60 publications) of global research on "AI-TCM". The USA's contributions are driven by its strong academic and industrial base in AI research, while India's focus on TCM aligns with its own traditional medical practices. These countries' involvement highlights the interdisciplinary nature of "AI-TCM" research, which draws from computer science, data analytics, and biomedical engineering.

The chord diagram's peripheral curve segments visually represent countries and regions. The length of each segment corresponds to the publication volume of the respective country or region [25]. The levels of collaboration between nations are reflected in their connectivity. Regarding global cooperation, China is most active, primarily collaborating with the USA (link strength = 43) and Australia (link strength = 21) (Fig. 3B). The high level of connectivity between these countries indicates a shared interest in exploring AI's potential to modernize TCM. For researchers, these collaboration networks offer valuable insights into potential strategic partnerships [27]. For instance, collaborating with institutions in China could provide access to large datasets and expertise in TCM, while partnerships with USA institutions could offer advanced AI technologies and computational resources. Industry practitioners, particularly those in the biotech and pharmaceutical sectors, can use this information to identify emerging trends and potential markets for AI-driven TCM products.

Identifying publications with substantial citation increases over time is crucial, achieved through recognizing citation bursts. Fig. 3C shows the citation spikes for the top 10 countries/regions with the strongest citation bursts, illustrated by the intensity of each spike with a red line. Notably, Australia experienced a substantial increase in citations (strength = 3.42) from 2018 to 2021, followed by France (strength = 3.05) and Italy (strength = 2.58), indicating these countries are emerging as key players in this field. This trend may be driven by factors such as growing interest in integrative medicine, available research funding, and strong academic institutions. Researchers can use this information to explore emerging topics in "AI-TCM" gaining traction in these countries.

3.2.2. Institutions

Researchers can gain valuable insights by identifying leading institutions and analyzing their citation surges to discover potential partners and funding sources. The dynamic research environment is reflected in a complex web of interconnected organizations. Over the past 24 years, significant progress has been made in the global study of "AI-TCM", involving more than 1,942 different entities. A connected network, shown in Fig. 4A, was established among these institutions, requiring at least seven publications to qualify. This network depicts individual institutions as circular nodes with text identifiers, while collaborative instances are represented by connecting lines. The intensity of collaboration is indicated by the thickness of lines, while the partnership strength is shown by the colors of the lines connecting an institution to its collaborators. The size of the circles correlates with the number of publications generated by each institution. A clustering map for the top 80 research institutions was generated using a minimum threshold of 5 publications per institution (Fig. 4B). Different color regions represent distinct clusters. The thickness of the lines between circles indicates the intensity of cooperation among institutions, while circle size corresponds to the number of documents published by each organization. Researchers can leverage these clusters to identify specialized areas of research and potential collaborative opportunities within their areas of interest. China Academy of Chinese Medical Sciences is the leading contributor, accounting for approximately 3.29 % (39 papers) of the total. Beijing University of Chinese Medicine and Shanghai University of Traditional Chinese Medicine follow closely with 3.04 % (36 papers) and 2.96 % (35 papers), respectively. The dominance of Chinese institutions in "AI-TCM" research, reflects the strategic emphasis placed by China on advancing this field. These institutions have significantly contributed to the field, making them key partners for future research. Our analysis of institutional collaboration shows Asia University's strong interest in partnerships, particularly its robust collaboration with Brigham and China Medical University Hospital (strength = 11). The active collaboration network in "AI-TCM" fosters a dynamic research environment that encourages innovation and the sharing of expertise. This environment provides an ideal platform for exchanging ideas, resources, and specialized skills. Scientists can leverage this network to stay updated on recent advancements, utilize shared resources, and enhance the quality of their research.

Identifying institutions with rising citation trends helps scholars find those with impactful research, paving the way for potential partnerships or funding. When evaluating partnerships, it is crucial to consider not only the quantity of research papers but also the enduring impact and adaptability of research efforts over time. CiteSpace analysis (Fig. 4C) revealed institutions with significant citation increases. For instance, the University of São Paulo experienced citation bursts from 2000 to 2006, peaking at 4.02. Asia University had prolonged citation bursts from 2011 to 2021, highlighting its sustained research strength, prominent position, and considerable academic influence in this field. However, the decline in citation bursts over the last three years suggests a potential shift in research focus or a decrease in research output, which may warrant further investigation. For researchers and industry practitioners, these citation bursts highlight institutions that are at the forefront of "AI-TCM" research and are likely to be engaged in cutting-edge projects. Partnering with such institutions can provide access to innovative research, advanced methodologies, and potential funding opportunities. Moreover, understanding the factors behind these citation bursts, such as groundbreaking publications, influential collaborations, or significant policy support, can offer insights into the key drivers of research success in "AI-TCM".

3.2.3. Authors

Identifying leading experts and examining their networks helps pinpoint key contributors in the field. Experts with high citation rates and a consistent publication record provide valuable insights that shape future research. Our analysis of "AI-TCM" authorship identified 6,626 key scholars, with fifteen researchers recognized for their prolific output, each authoring at least two papers. These scholars, likely possessing significant expertise, are crucial for advancing "AI-TCM" research. To further explore collaboration patterns, we used VOSviewer to create visual diagrams, setting a minimum of two publications per author. The size of the nodes represents the publication count, and different colors indicate author categories. The strength of collaborative interactions is shown by the links between nodes. Notably, 93 authors exceeded the publication threshold, with Calvin Yu-Chian Chen and Hsin-Yi Chen demonstrating the strongest collaborative relationships (Fig. 5A). Additionally, Wang Yu (1.09 %, 13 publications), Calvin Yu-Chian Chen (1.01 %, 12 publications), and Hsin-Yi Chen (0.68 %, 8 publications) were identified as prolific contributors in "AI-TCM" research, highlighting their significant impact.

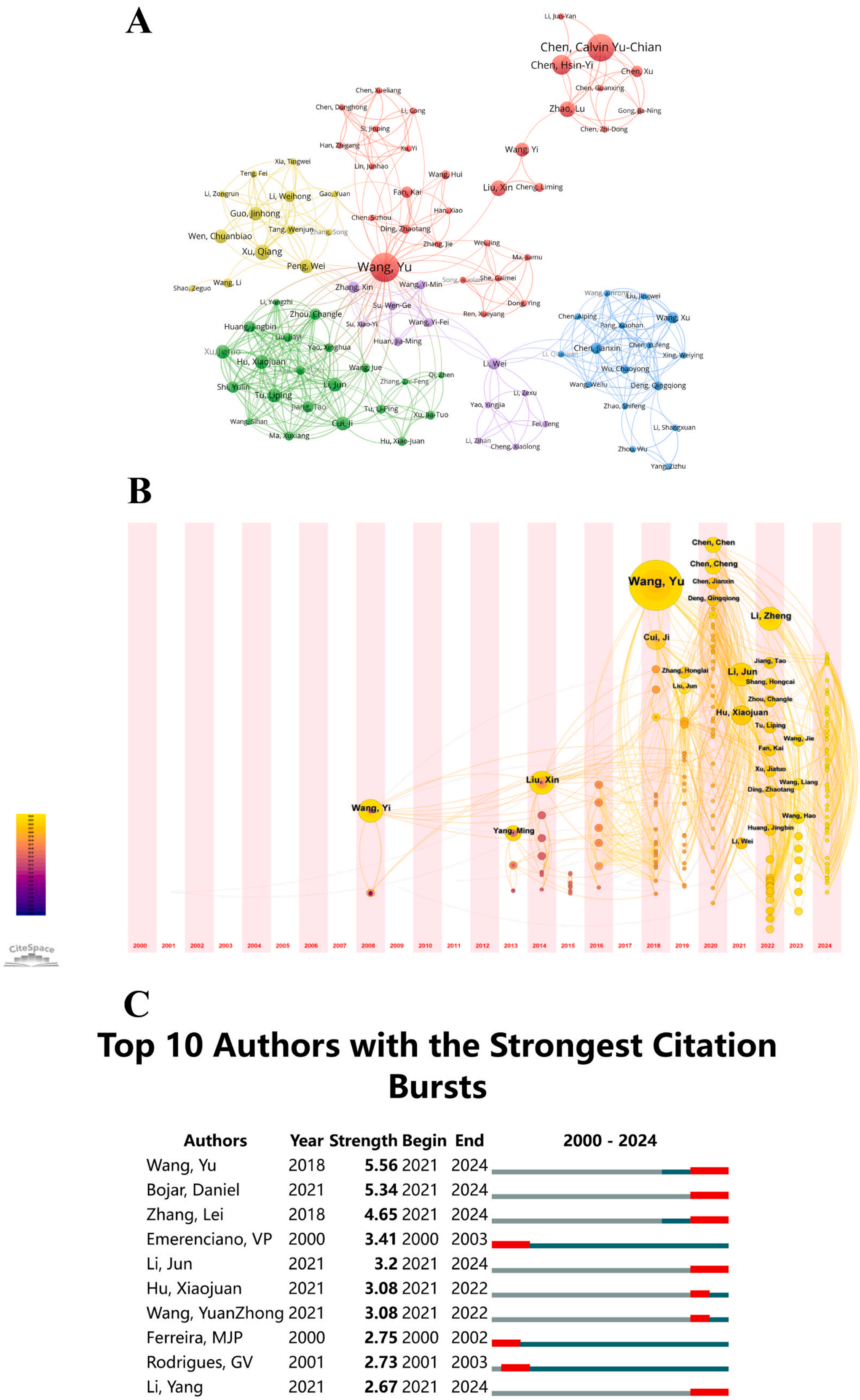
A detailed examination of various nodes was conducted over the same period. In the diagram, each node represents an author, with its size indicating their publication volume. The timeframe corresponds to when the author first published. Purple indicates early work, while yellow shows recent publications. Overlapping colors suggest multiple publications within the same year, with a greater overlap indicating consistent and substantial output (Fig. 5B). Wang Yu, Wang Yi, and Li Zheng have maintained high research output over time. Connections between nodes across different time zones indicate co-occurrence relationships among authors. Since 2013, the number of authors in this field has gradually increased, peaking in 2020 with the most new authors. The temporal overlap of publications, as indicated by the color gradients, showcases the continuous and collaborative nature of research in "AI-TCM". The connections between nodes in different time zones further illustrate the co-occurrence relationships among authors, reflecting the interdisciplinary and collaborative nature of the research. This growing trend of collaboration is indicative of a vibrant research environment where knowledge and expertise are actively shared.

Studying citation bursts is crucial for understanding how frequently authors are cited within a specific field during a given timeframe [28,29]. Fig. 5C ranks the top ten authors with the highest citation counts in "AI-TCM". The figure shows that Wang Yu experienced a citation burst from 2021 to 2024, with a peak burst strength of 5.56. Most of the top 10 citation bursts began after 2021, indicating a surge of interest in "AI-TCM" research from 2021 to 2024. The foundational work laid out by these scholars provides a robust platform for future research. Their influential studies set the stage for subsequent investigations, ensuring that the field continues to evolve and expand. For researchers entering the "AI-TCM" domain, these prominent scholars serve as critical guides, offering valuable insights into key trends and potential areas of exploration. Additionally, for professionals in the field, understanding these citation patterns can inform strategic decisions, such as identifying potential collaborators or focusing on emerging research topics.

3.3. Journals, related fields, and Co-cited references

3.3.1. Journals & related fields

Visualization of journal publication data offers insights into the scholarly communication landscape across 559 journals featuring articles on AI applications in TCM. A heat-based graph, created using thermodynamics, determined that each journal must have at least



(caption on next page)

Fig. 5. (A) Network of collaboration between authors. Circles and text labels constitute a node, where diverse colors denote distinct clusters. The thickness of lines connecting the circles indicates the strength of cooperation among authors, while the size of the circle positively correlates with the number of articles published by the author. (B) Temporal overlay of the authors' cooperative network. Each sphere symbolizes an author, and the aggregate size of overlapping spheres, representing the sum of their sizes along the yearly ring line, corresponds to the total number of articles authored. Purple-red signifies earlier publications by the author, while yellow indicates recent publications, and overlapping colors denote publications spanning multiple years. Overlapping colors on the spheres create a ring-like pattern. Connections between nodes in temporal zones depict collaborative occurrences among authors. (C) Top 10 authors with the strongest citation bursts in publications related to "artificial intelligence-Traditional Chinese Medicine". "Burst" refers to a sudden increase in a research topic's prominence within a specific time period. BurstBegin marks the start of this phenomenon, signifying the onset of significant growth, while BurstEnd marks the conclusion, indicating when the growth trend slows or declines. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

four papers to show document distribution. The color depth on the graph represents the number of papers published in each journal (Fig. 6A), guiding researchers in selecting appropriate journals for publication. *Molecules* leads with 26 publications, followed by *Evidence-Based Complementary* and *Alternative Medicine* (n = 25), *IEEE Access* (n = 25), and *Scientific Reports* (n = 25). Identifying top journals and their citation rates provides valuable information for researchers evaluating the impact of their work and selecting potential publication outlets.

Fig. 6B uses different colors to represent journals of varying emergence years. Circle size and label frequency indicate occurrence frequency, while circle color represents the mean publication year. *BMC Bioinformatics* has a long publishing history, while *Advanced Science* and *Heliyon* are emerging journals, highlighted in yellow. Fig. 6C further identifies the top ten journals that have seen significant citation increases in "AI-TCM" research.

The overlay of dual-maps in journals effectively showcases the shifting locations of scientific research centers and the distribution of journals across various fields [30]. The map labels indicate different research zones covered in the papers. Journals citing other publications appear on the right, while those referencing alternate sources are on the left. Distinct colored lines visually represent citation pathways, with the intensity of these connections determined by citation frequency (z-score scale) [21]. This visualization helps identify emerging trends and shifts in scientific focus, guiding researchers in effectively targeting their efforts. Fig. 6D shows that "AI-TCM" studies are mainly concentrated in eight major areas: physics, materials science, chemistry, molecular biology, immunology, environmental toxicology, genetics, and nutrition. This interdisciplinary focus reflects the field's broad scientific impact, as "AI-TCM" research draws on diverse knowledge areas to address complex health challenges. The shifts in scientific focus, as indicated by the frequency and intensity of citations, suggest that "AI-TCM" is gaining traction across multiple fields, potentially influencing the direction of future research and innovation.

VOSviewer software was used to visually analyze 1,183 articles, categorizing them into five primary fields. This classification deepens the understanding of research domains and their interrelations, providing valuable insights for researchers and industry professionals navigating the evolving landscape of AI in TCM. The clustering is visualized in Fig. 6E, with different-colored spheres representing various domains. The results indicate that a significant portion of related studies are focused on "Biology and Medicine", with many papers in categories like "Food Science & Technology", "Biochemistry & Molecular Biology", and "Pharmacology & Pharmacy". The focus on "Biology and Medicine" underscores the field's potential to revolutionize healthcare by integrating AI with TCM practices. The strong representation of studies in "Food Science & Technology" and related fields suggests that "AI-TCM" research is not only advancing traditional medicine but also exploring its applications in nutrition and wellness, areas that are increasingly recognized for their importance in preventive healthcare.

The insights gained from journal publication data, citation dynamics, and research clustering offer valuable guidance for future research and development in the "AI-TCM" field, ultimately driving innovation and progress in the advancement of TCM through the application of AI.

3.3.2. Co-cited references

By identifying the most frequently referenced and impactful publications, researchers can enhance their understanding of the field and make more informed decisions about where to focus their efforts. Fig. 7A displays a co-citation network diagram of scholarly articles related to "AI-TCM" from January 1, 2000, to March 1, 2024, analyzed using CiteSpace. The sizes of the circles reflect their co-citation frequencies over the years. The color scale ranges from purple (older citations) to yellow (more recent citations). Merged colors on circles indicate consistent citations across the years. The circles' connections represent co-citation relationships among various publications. Pink-highlighted nodes indicate crucial network points with a centrality exceeding 0.1. The most highly cited work is 'ImageNet classification with deep convolutional neural networks' by Krizhevsky et al., published in *Communications of the ACM* in 2017, with the highest co-citation count (n = 24) [31]. This work, which is at the forefront of AI research, laid the foundation for subsequent studies in AI applications, including those in TCM. Fig. 7A displays a co-citation network diagram, revealing connections within the research literature and highlighting key publications and their influence over time. By recognizing these influential publications, researchers can gain a deeper understanding of the core concepts and methodologies that have driven the field forward. This understanding allows them to build upon established knowledge, explore emerging trends, and prioritize areas for further investigation. Additionally, the consistent citations of certain works over the years, as indicated by the merging colors on the circles, suggest that these publications remain relevant and continue to inform current research.

CiteSpace was used to analyze citation bursts in "AI-TCM" research. Fig. 7B illustrates the impact of the top 20 references, highlighting significant scholarly attention. Among the top 20 references with significant citation spikes, most papers saw a notable increase in citation counts from 2018 to 2024. This indicates a growing interest in the subject area after 2018. This trend can be

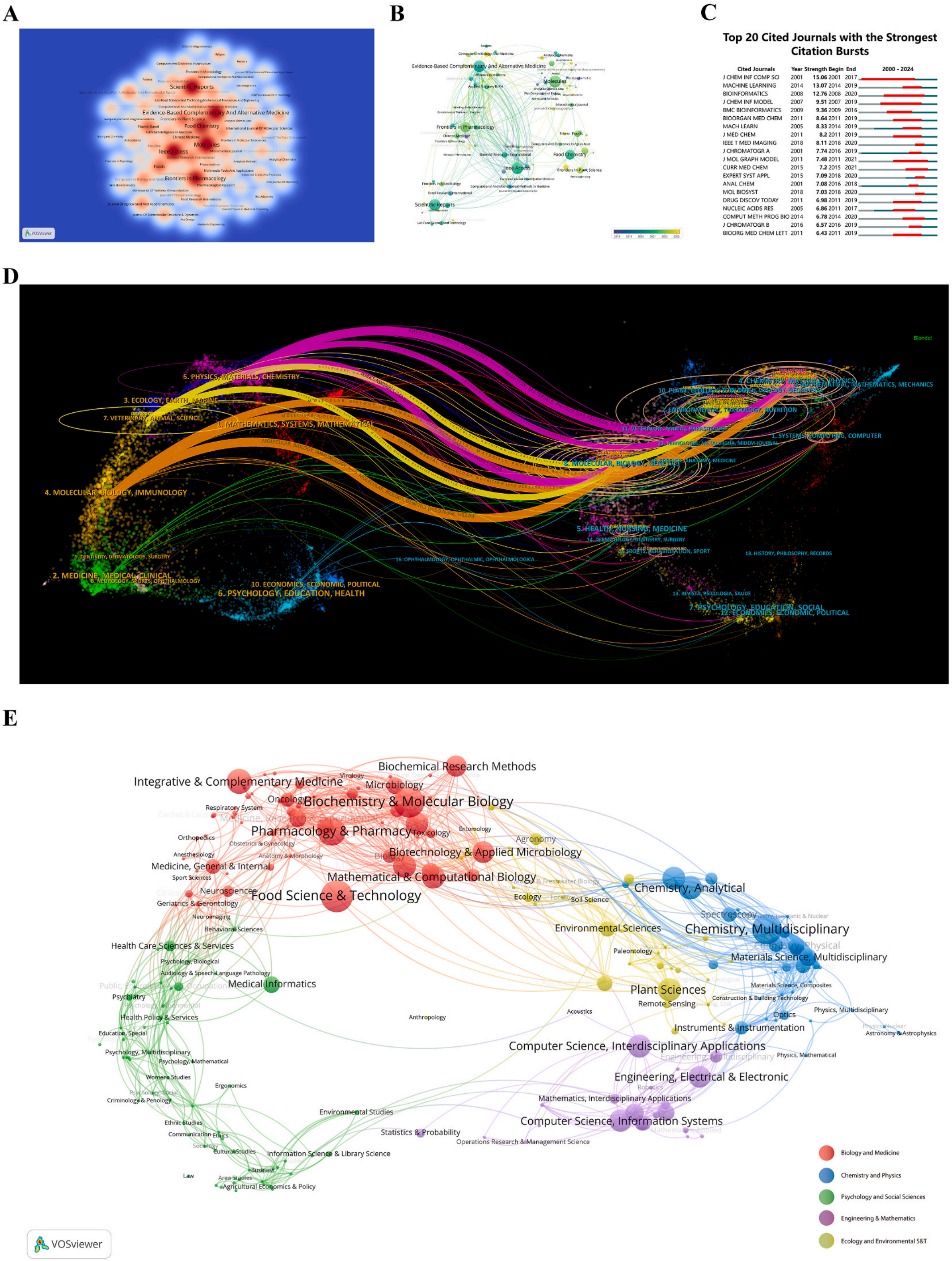


Fig. 6. (A) Density visualization map of journal citations. The color intensity correlates directly with the volume of publications. (B) Journal distribution based on the average publication year (blue: earlier, yellow: later). Each circle and its label together create a node, where the circle size directly relates to the frequency of the keyword's occurrence. The color gradient of each circle in the lower right corner denotes the average year of publication. (C) Top 20 journals with the most significant citation bursts. "Burst" refers to a sudden increase in a research topic's prominence within a specific time period. BurstBegin marks the start of this phenomenon, signifying the onset of significant growth, while BurstEnd marks the conclusion, indicating when the growth trend slows or declines. (D) A dual-map overlay of journals related to artificial intelligence in Traditional Chinese Medicine. Each point in the graph signifies a journal, while the curves bridging the left and right parts of the graph represent citation connections. These trajectories offer insights into interdisciplinary relationships within the field and vividly showcase the inception and progression of citations. (E) Analyses of research subject areas. Various colored spheres symbolize distinct converging fields. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

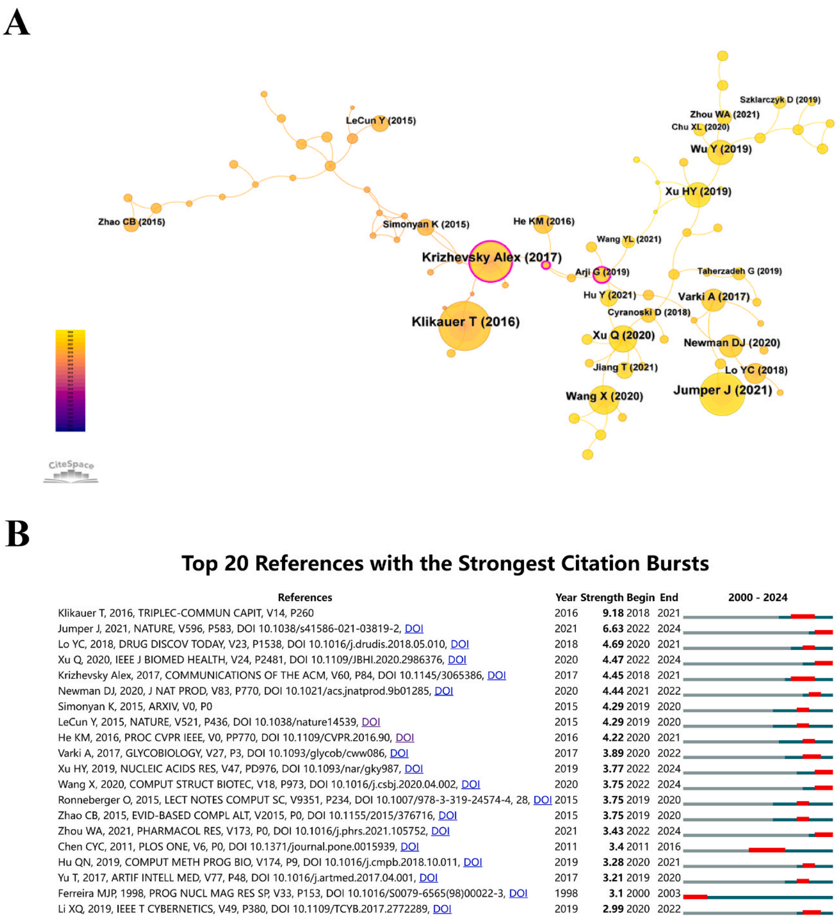


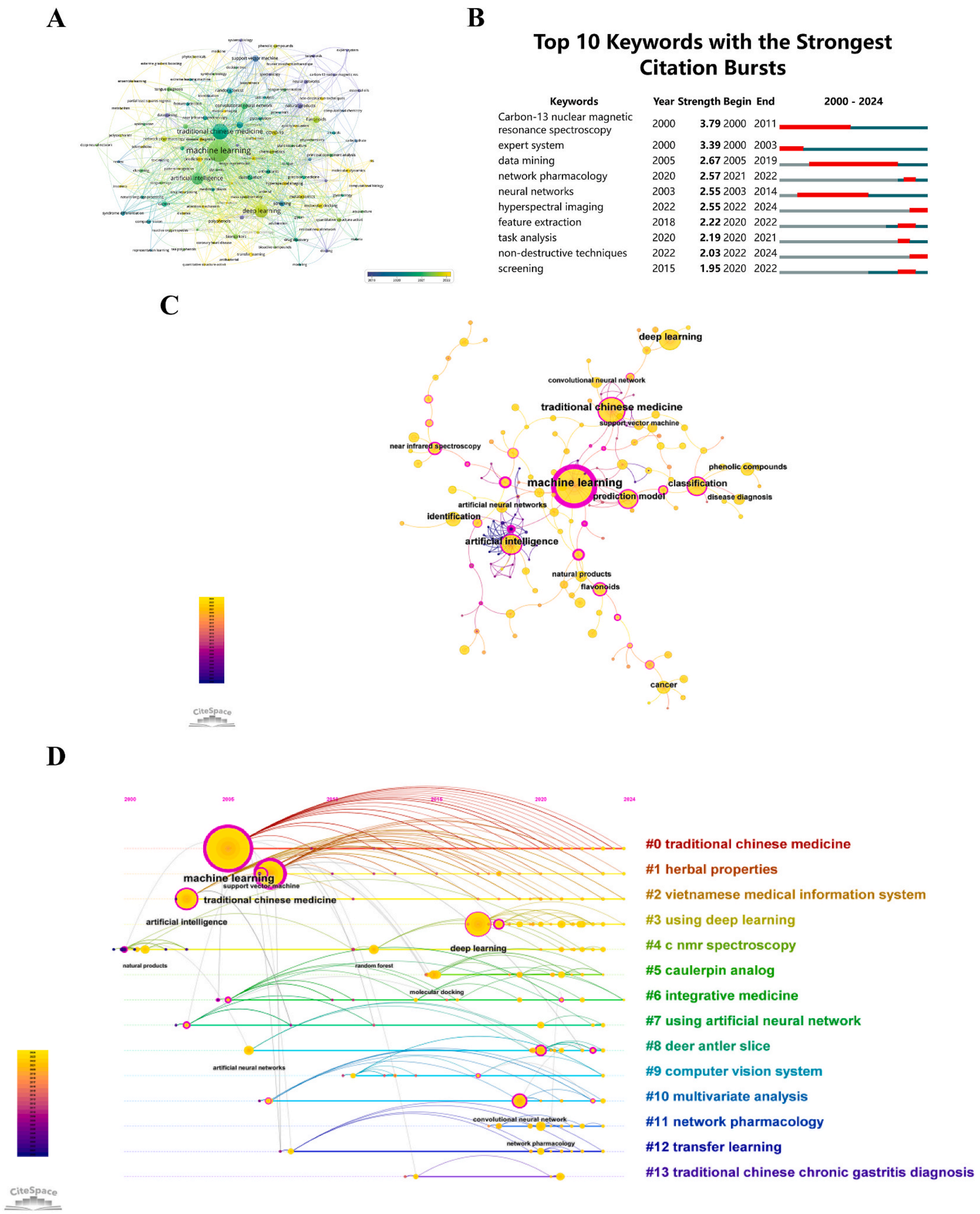
Fig. 7. (A) Co-citation analysis chart for "artificial intelligence-Traditional Chinese Medicine". The sizes of the overlaid circles, corresponding to the sizes of the circles on the annual rings, are proportional to the number of citations. Purple indicates earlier citation times, while yellow indicates later citation times. Overlapping colors indicate citations in corresponding years. The lines connecting the circles represent the co-citation situation of the literature, with nodes marked in magenta indicating critical nodes with a centrality greater than 0.1. (B) Top 20 references with the highest citation bursts. "Burst" refers to a sudden increase in a research topic's prominence within a specific time period. BurstBegin marks the start of this phenomenon, signifying the onset of significant growth, while BurstEnd marks the conclusion, indicating when the growth trend slows or declines. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

attributed to several factors. First, the rapid advancements in AI technologies have made them more accessible and applicable to complex medical problems, including those related to TCM. Second, the increasing global interest in alternative and complementary medicine, coupled with the push for evidence-based practices, has driven researchers to explore the potential of AI in validating and enhancing TCM. For researchers, the identification of citation bursts serves as a roadmap for adapting their research agendas to align with emerging trends. By focusing on topics that are gaining traction, researchers can ensure that their work remains relevant and contributes meaningfully to the ongoing discourse in the "AI-TCM" domain. This strategic alignment is essential for advancing the field and for the practical application of research findings in clinical and policy settings. For industry practitioners, the insights gained from understanding citation trends and co-citation networks can inform decision-making processes, such as investment strategies and product development initiatives. By aligning with emerging research trends, practitioners can capitalize on new opportunities and maintain a competitive edge in the rapidly evolving field of "AI-TCM".

3.4. Keywords

VOSviewer was used for clustering analysis based on keyword co-occurrence, with a minimum threshold of four occurrences. The visualization included only keywords meeting this requirement from a total of 3568 unique keywords (excluding duplicates). A total of 117 keywords were selected for network representation in Fig. 8A. The graph in Fig. 8A depicts temporal trends in word frequency, with each node represented by a circle and label. The size of each circle corresponds to keyword frequency, and the connection thickness indicates the strength of relationships. The color of each circle, shown in the lower right corner, represents the average year of occurrence. Blue indicates earlier appearances, and yellow signifies later ones. Early research efforts focused on the application of machine learning techniques such as support vector machines and the exploration of natural products. However, more recent studies have shifted towards advanced topics like prediction models and molecular dynamics, reflecting the maturation of the field and the growing complexity of AI applications in TCM. Identifying prevalent keywords and their temporal patterns helps researchers understand the shifting landscape of research interests and prioritize areas for further investigation.

Fig. 8B displays keyword bursts, particularly those with significant citation surges. This analysis emphasizes research areas that have garnered significant scholarly attention. Examining temporal patterns of keyword bursts can guide decisions on investment and collaboration, aligning with current research trends and fostering strategic partnerships. As shown in Fig. 8B, the keyword with the highest citation burst intensity is ‘Carbon-13 nuclear magnetic resonance spectroscopy’, with a burst strength of 3.79 from 2000 to



(caption on next page)

Fig. 8. (A) Visualization of keyword intensity overlay over time. Each circle and its label constitute a node, where the circle size corresponds positively to the frequency of keyword occurrence. The color gradient in the lower right corner denotes the average year of occurrence, with blue representing relatively early keywords and yellow indicating recently emerged keywords that may lead to new research directions. (B) Top 10 keywords with the strongest citation bursts identified by CiteSpace. "Burst" refers to a sudden increase in a research topic's prominence within a specific time period. BurstBegin marks the start of this phenomenon, signifying the onset of significant growth, while BurstEnd marks the conclusion, indicating when the growth trend slows or declines. (C) Co-occurrence analysis chart of keyword frequencies. The sizes of the overlaid circles, corresponding to the sizes of the circles on the annual rings, are proportional to the number of citations. Purple indicates earlier citation times, yellow indicates later citation times, and overlapping colors indicate citations in corresponding years. The lines connecting the circles represent the co-citation situation of the literature, and the nodes marked in magenta are critical nodes with a centrality greater than 0.1. (D) Temporal trends in keyword co-occurrence. The sizes of the overlaid circles, corresponding to the sizes of the circles on the annual rings, are proportional to the frequency of keywords. The lines between keywords represent co-occurrence. Purple represents the relatively early appearance time of keywords, yellow represents the later appearance time of keywords, and overlapping colors indicate that keywords appeared in the corresponding years. Magenta nodes are nodes with relatively strong centrality, located at the central position and acting as hubs. Keywords in the same cluster are placed on the same horizontal line. The first appearance time of keywords is placed at the top of the view, with time progressing towards the right. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

2011. The keyword 'data mining' exhibited the longest citation burst, sustained over 14 years. Notably, among the top 10 keywords with citation bursts, 'hyperspectral imaging' and 'non-destructive techniques' showed bursts after 2023, suggesting these are emerging hot topics in the field.

Co-occurrence analysis reveals crucial connections between keywords, highlighting key themes in the field. Using CiteSpace, the co-occurrence of "AI-TCM" keywords from January 1, 2000, to March 1, 2024, was examined, as shown in Fig. 8C. The chart's circles represent the cumulative frequency of keyword usage each year, with purple circles indicating earlier appearances and yellow circles representing more recent ones. Mixed colors reflect citations spanning various years. The lines between circles depict co-citation links between references. Magenta nodes highlight significant keywords with centrality scores above 0.1. In Fig. 8C, 'machine learning' is the most frequently co-occurring keyword, followed by 'traditional Chinese medicine' and 'deep learning'. These terms not only represent the central themes in "AI-TCM" research but also indicate the interdisciplinary nature of the field, where traditional medical knowledge is being integrated with cutting-edge AI technologies.

Analyzing the evolving patterns and key focuses in "AI-TCM" research is essential for making informed decisions on funding and collaborations, ensuring alignment with current research priorities. Fig. 8D shows a timeline that clusters keyword frequencies in major research areas. The diagram uses circles of varying sizes to represent keyword frequency each year, with connections indicating co-occurrence. The color scheme is informative: purple for earlier keywords, yellow for recent ones, and mixed colors for consistent keywords over time. Rose-colored nodes highlight important keywords with central relevance in the network. Keywords in each cluster are organized horizontally, progressing chronologically from left to right. This visual representation helps to understand keyword distribution within clusters, with larger sizes indicating greater significance. It also shows the temporal span of keywords within each cluster. The keywords are grouped into 14 clusters, including: #0 traditional Chinese medicine, #1 herbal properties, #2 vietnamese medical information system, #3 using deep learning, #4 carbon-13 nuclear magnetic resonance spectroscopy, #5 caulerpin analog, #6 integrative medicine, #7 using artificial neural network, #8 deer antler slice, #9 computer vision system, #10 multivariate analysis, #11 network pharmacology, #12 transfer learning, #13 traditional Chinese chronic gastritis diagnosis. These trends are critical for researchers and industry practitioners alike, as they indicate potential directions for future investigations and investments.

3.5. Related diseases

Understanding the diseases most closely associated with "AI-TCM" research allows researchers to focus on specific medical conditions. This targeted approach could accelerate the development of pharmaceuticals and treatments, increasing the likelihood of more effective therapies. The Citexs Data Platform identified 993 diseases from 1,183 articles, each referenced by at least nine articles. These diseases were visualized in a VOSviewer-generated heatmap, showing the frequency and interconnections of diseases related to "AI-TCM" research (Fig. 9A). The top five most frequently mentioned diseases include hepatocellular carcinoma, chemical and drug-induced liver damage, Papillon-Lefèvre disease, Parkinson's disease, and anorexia. This focus may be driven by the prevalence of these diseases in regions where TCM is widely practiced, as well as the potential for TCM to offer alternative or complementary treatments to conventional therapies. Additionally, a co-occurrence-based cluster analysis was performed using VOSviewer, with each disease requiring at least five instances (Fig. 9B). In this visualization, the size of the circles and labels indicates disease occurrence, while the thickness of connecting lines represents the strength of connections between diseases. Different colors signify distinct clusters related to specific disease groupings. By identifying clusters of related diseases, researchers can also prioritize their efforts on investigating these groupings, potentially uncovering novel insights into the etiology and treatment of multiple conditions simultaneously. This approach aligns with the holistic nature of TCM, where treatment often addresses multiple symptoms or conditions at once.

The findings have significant implications for both researchers and industry practitioners in the "AI-TCM" field. By identifying the illnesses most commonly associated with "AI-TCM" studies, scientists can strategically focus on understanding and addressing specific health issues. This approach could accelerate the development of customized medications and treatments for these medical conditions. For industry practitioners, understanding the "AI-TCM" research landscape can guide decisions in drug development, treatment strategies, and resource allocation. Tools like VOSviewer, which visualize disease frequency and relationships, offer valuable insights

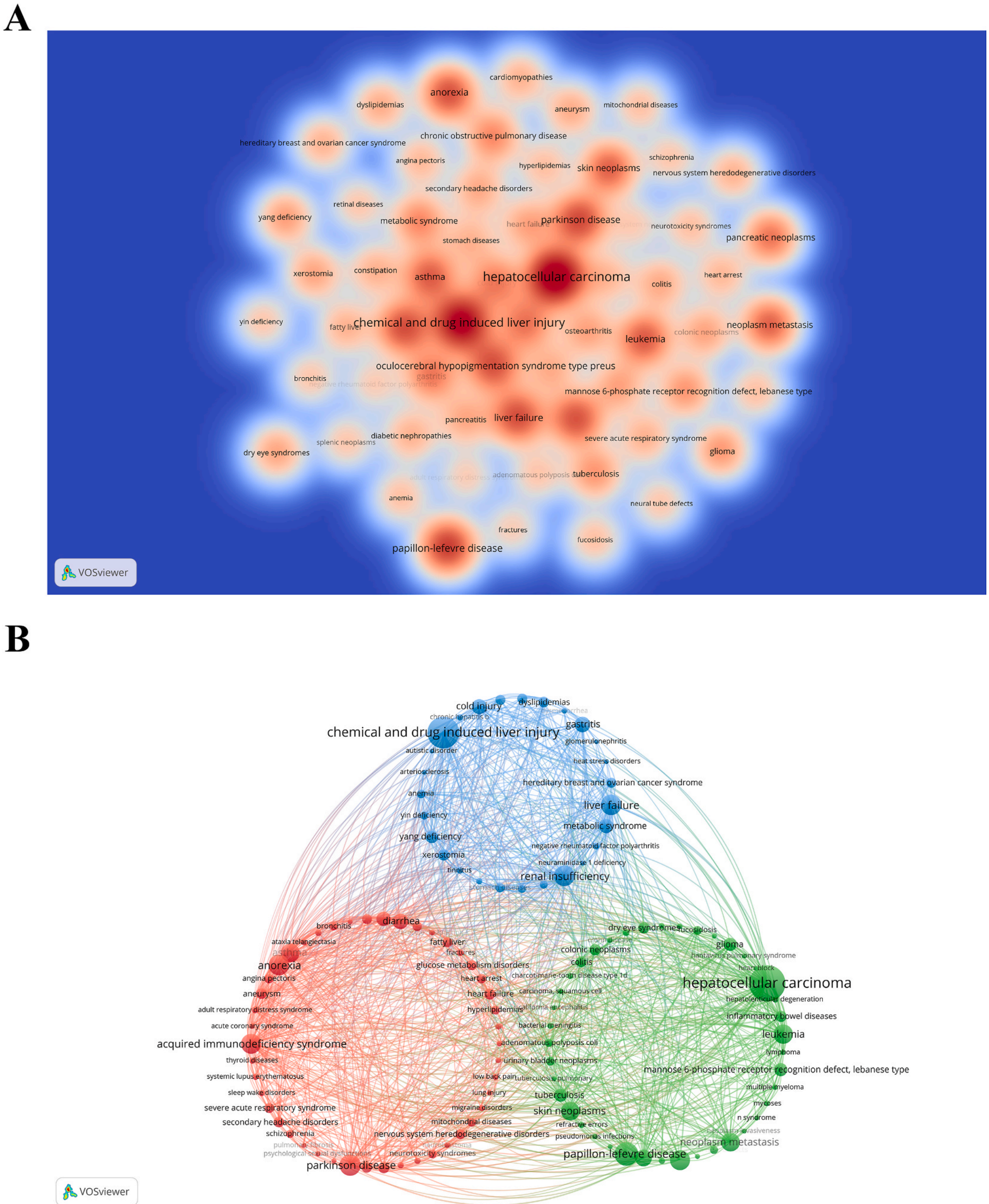


Fig. 9. (A) Density visualization map of associated diseases. The intensity of color is directly proportional to the frequency of occurrence of the represented disease. (B) Disease clustering analysis chart. Nodes of different colors form distinct clusters, with each color representing a specific disease cluster, indicative of particular biological or medical fields or groups of diseases. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

into the prevalence and interconnections of diseases in "AI-TCM", aiding researchers and practitioners in navigating this complex field and fostering collaborations for advancing medical interventions.

3.6. *Opportunities, challenges, and Recommendations*

3.6.1. *Opportunities*

TCM represents centuries of valuable experience and innovation in medical practice. As an evolving healthcare system, it has shown strengths in various health areas. The main barrier to TCM's global acceptance is the limited scientific evidence. However, AI serves as a bridge between TCM and modern science and technology. AI enables TCM diagnostics and treatments to be more quantified, objective, and standardized. Additionally, AI technology significantly advances TCM theory. AI-assisted TCM diagnosis using digital signal datasets can bring TCM diagnostic methods closer to those of western medicine. With AI assistance, more scientific evidence about TCM is likely to emerge. AI excels in examining complex data sets, facilitating the evaluation and validation of TCM theories. It supports TCM modernization efforts, including AI-assisted virtual drug screening and prediction of absorption, distribution, metabolism, excretion, and toxicity of potential candidates [11].

AI also enables personalized TCM treatments. By analyzing symptoms, medical history, and health metrics, AI models can suggest tailored herbal formulas and acupoint prescriptions that align with a patient's TCM pattern differentiation [32], highlighting the personalized nature of TCM practice. Additionally, AI facilitates in-depth data analysis to uncover new TCM insights from clinical practice [7]. Using machine learning algorithms on herbal medicine databases, researchers have identified innovative herb combinations and network pharmacology relationships [33,34]. AI offers new opportunities and advanced tools to enhance TCM research, clinical practice, and model validation through scientific methods. As AI and TCM integration advances, practitioners gain new opportunities for growth. Practitioners can use AI to enhance training programs and engage in modern validation efforts. Digital platforms provide a wider scope for promoting TCM's unique roles in preventive care and healthcare. Considering the future of TCM practitioners, one must acknowledge its rich historical wisdom. TCM embodies centuries of invaluable medical practice experience, serving as an essential repository of knowledge. The integration of AI and TCM holds potential to advance and modernize TCM while preserving its core holistic principles.

3.6.2. Challenges

The application of AI in TCM faces significant challenges and constraints. Limited access to TCM terminology, the complexity of TCM theory, and the lack of an organized digital archive of medical records remain major obstacles for AI-supported TCM research. Currently, Chinese scholars lead "AI-TCM" research, largely due to the scarcity of TCM expertise and language barriers for international researchers. Mastering TCM domain knowledge is a significant challenge for AI practitioners, even those from China. Integrating TCM with AI technology is impossible without a solid understanding of TCM theory. While there have been collaborative efforts between Chinese and foreign experts on AI-assisted TCM diagnosis and treatment [35–38], independent AI-supported TCM initiatives in Japan and South Korea remain limited. These efforts mostly rely on digital signal data and clinical examinations, with less focus on TCM domain knowledge [39,40]. As digital TCM advances and converges with western medicine, further modernization of TCM will require international collaboration to promote global acceptance of TCM principles and practices.

Moreover, the significance of developing effective human-computer interactions and improving user experience in AI implementation within TCM is emphasized by concerns that AI could erode the "human touch" typically associated with physicians [41]. This concern reflects the common fear that AI might reduce doctor-patient communication, potentially weakening the therapeutic alliance and diminishing crucial relational aspects like empathy and understanding, which are essential to patient-centered care. Although AI positively influences many aspects of TCM research, it is essential to acknowledge the human element, as TCM care is ultimately delivered to individuals. Emphasizing shared decision-making (SDM) as a strategy for bridging gaps in evidence-based practice, it highlights placing the patient at the center and encourages patient involvement in discussions about diagnosis, treatment, and follow-up. This approach helps develop customized clinical decisions that meet patient needs [42,43]. The impact of AI on SDM remains uncertain, and its implementation presents various risks and challenges. Currently, AI cannot fully personalize clinical decisions in collaboration with patients within the TCM sector. Further research is needed to determine if AI-supported decision-making can alleviate patient decision dilemmas, increase patient knowledge, and improve satisfaction. Currently, AI in the TCM field lacks the capability to achieve personalized clinical decision-making with patients [9].

In TCM diagnosis and treatment, the presence of a human specialist is essential. Only a human TCM practitioner can interpret the seven emotions experienced by patients. These emotions include happiness, anger, worry, contemplation, sadness, fear, and surprise, which typically do not cause disease. However, excessive or prolonged emotional triggers can disrupt organ harmony, disturb the Yin-Yang balance, and affect the flow of qi and blood, leading to illness. Current AI development struggles to understand the complexity of human emotions, let alone enable scientific TCM diagnosis based on emotions. AI mainly enhances certain cognitive abilities but cannot replace human thought processes. Additionally, AI-supported decisions can create personalized risk assessments using data from sources like electronic health records. However, differences between training data and target populations, or insufficient data, can lead to biases or unfair treatment [17].

The legal framework for addressing medical disputes from AI-assisted TCM diagnoses lacks clear definitions or provisions [44]. Although AI diagnostics currently surpass physicians in speed and may achieve high clinical accuracy, establishing accountability mechanisms for errors is crucial. A recent study on AI in healthcare emphasized the need for clear accountability in developing medical AI [45]. Chinese laws on no-fault compensation only address specific errors, excluding complications and accidents, thus releasing healthcare institutions from liability. Additionally, data collected by intelligent diagnostic robots lacks legal protection [46]. The growing integration of AI in clinical settings will result in accumulating vast amounts of personal health information, highlighting gaps in health information laws, data ownership uncertainties, and limited public understanding of privacy rights. This situation raises concerns about security risks due to incomplete governance structures. The rise of technologies like "intelligent surgical robots" and "AI-supported TCM diagnostics" necessitates new institutional and legal frameworks.

3.6.3. Recommendations

Advancing the integration of AI and TCM requires a multifaceted approach. First, establishing a high-quality public TCM database is essential. The quality and quantity of available data are crucial for shaping model training outcomes. Currently, publicly accessible datasets are scarce. Therefore, creating expansive and standardized TCM diagnostic datasets is crucial for advancing this field. Encouraging researchers to share datasets publicly will significantly accelerate progress in related studies. Second, improving hardware and implementing an intelligent TCM diagnostic information collection platform are essential steps. Enhancing data collection and processing technology will expedite efficient TCM diagnostic information gathering. Efforts should also standardize TCM diagnostic techniques and guidelines, establish further standards, and achieve data objectification and standardization. Third, fostering collaboration between TCM practitioners and information technology (IT) experts is vital for accelerating AI model innovation. Developing AI models with multi-label and multi-modality capabilities will better suit TCM diagnostic characteristics and align with actual clinical needs. Additionally, exploring model generalizability and interpretability is essential. Fourth, integrating principles of both traditional Chinese and western medicine into AI-based TCM diagnosis research is crucial. In hospital settings, TCM diagnosis often requires integration with medical test results. Incorporating modern medical examination data into "AI-TCM" studies may reveal new opportunities. Fifth, expanding AI research in TCM diagnosis to better meet clinical demands is essential. Finally, exploring lightweight networks, developing portable diagnostic equipment, and establishing instant care systems are imperative. Using wearable devices and smartphones can streamline TCM health assessment.

3.7. Strengths & limitations

Compared to previous research relying on meta-analyses or narrative reviews, this study's use of bibliometric tools provided a more comprehensive insight into research trends and focal areas [47]. Over the past 24 years, this study is the first to conduct a bibliometric analysis, mapping the "AI-TCM" knowledge landscape. Despite certain limitations, it offers a broad and objective reference for future advancements.

This study faced several limitations. First, due to CiteSpace limitations, publications were extracted only from WoSCC, leading to unavoidable selection bias. Second, using citation count to measure a paper's impact is subject to various confounding factors, potentially affecting accuracy. Third, the large volume of papers may have compromised the study's credibility by limiting the feasibility of thoroughly analyzing each paper and subfield. Fourth, as shown in previous bibliometric studies, these techniques rely heavily on natural language processing, which could introduce bias [47–52]. Fifth, as the birthplace of TCM, China has produced a significant body of research in this field, much of it published in Chinese. However, due to differences in database coverage and literature format between Chinese and English sources, detailed bibliometric analysis presents unavoidable methodological challenges. Consequently, this study only included English-language publications, which may introduce inevitable publication and reporting biases. Lastly, incomplete literature collection may have led to the omission of newly published studies and certain keywords in the statistical analysis.

4. Conclusion

Internet and AI technologies have profoundly impacted and continue to change how people live. In the AI era, TCM must be both preserved and actively adapted for development. Through bibliometric analysis, this study explores the "AI-TCM" domain, investigating international collaboration, publication trends, and key research themes. The findings provide guidance for further research on novel AI approaches and strategies in TCM study and implementation. Although AI technology has introduced new possibilities and advances for TCM, it is crucial to acknowledge its constraints and challenges in modern TCM application. To ensure TCM continues to benefit society in the future, researchers must stay updated on trends, utilize existing knowledge, take proactive measures, seize opportunities, collaborate across disciplines with IT experts, and aim for breakthroughs in TCM development within the AI era.

Data availability statement

Data will be provided upon reasonable request.

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Ethics statement

Since the data used in this study were publicly available and did not involve human subjects, ethical approval or informed consent was not required.

CRediT authorship contribution statement

Siyang Cao: Writing – original draft, Formal analysis, Conceptualization. **Yihao Wei:** Writing – original draft, Investigation, Data curation. **Yaohang Yue:** Writing – review & editing, Software, Methodology. **Deli Wang:** Writing – review & editing, Software, Methodology. **Ao Xiong:** Supervision, Project administration, Funding acquisition. **Jun Yang:** Supervision, Project administration, Funding acquisition. **Hui Zeng:** Supervision, Project administration, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.heliyon.2024.e37439.

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