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Information fusion and artificial intelligence for smart healthcare: a bibliometric study

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ABSTRACT

With the fast progress in information technologies and artificial intelligence (AI), smart healthcare has gained considerable momentum. By using advanced technologies like AI, smart healthcare aims to promote human beings' health and well-being throughout their life. As smart healthcare develops, big healthcare data are produced by various sensors, devices, and communication technologies constantly. To deal with these big multi-source data, automatic information fusion becomes crucial. Information fusion refers to the integration of multiple information sources for obtaining more reliable, effective, and precise information to support optimal decision-making. The close study of information fusion for healthcare with the adoption of advanced AI technologies has become an increasingly important and active field of research. The aim of this is to present a systematic description and state-of-the-art understanding of research about information fusion for healthcare with AI. Structural topic modeling was implemented to detect major research topics covered within 351 relevant articles. Annual trends and correlations of the identified topics were also investigated to identify potential future research directions. In addition, the primary research concerns of top countries/regions, institutions, and authors were shown and compared. The findings based on our analyses provide scientific and technological perspectives of research on information fusion for smart health with AI and offer useful insights and implications for its future development. We also provide valuable guidance for researchers and project managers to allocate research resources and promote effective international collaborations.

1. Introduction

The fast advances in information technologies, artificial intelligence (AI), sensors, and wearable devices promote enormous opportunities for healthcare improvement (e.g., Chi et al., 2020; Thaker et al., 2020; Wang et al., 2021; Khan et al., 2021). The notion of smart healthcare has gradually gained momentum. Smart healthcare employs advanced technologies like AI, the Internet of Things, big data, wearable devices, and mobile Internet to develop intelligent healthcare systems with high levels of efficiency, reliability, and

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List of abbreviations and their full names

1-D	one-dimensional
2-D	two-dimensional
3-D	three-dimensional
ACP	average citations per article
AI	artificial intelligence
C/Y	annual citations
CNN	convolutional neural network
CRP	chained residual pooling
CT	computed tomography
CVD	Cardiovascular disease
DCE	dynamic contrast-enhanced
DDL	dense deconvolutional layer
DNN	deep neural network
DWT	discrete wavelet transform
ECG	electrocardiograms
EEG	electroencephalography
EEG	electroencephalogram
EMG	electromyogram
FCN	fully convolutional network
FDG	fluoro-D-glucose
fMRI	functional magnetic resonance imaging
FREX	frequent and exclusive terms
HCC	hepatocellular carcinoma
h-index	Hirsch index
ICA	independent component analysis
LSTM	long short-term memory
MCF	multichannel fusion
MCI	mild cognitive impairment
MDC	multi-domain connectome
MK	Mann-Kendall
MLW	multi-weighted
MRI	magnetic resonance imaging
PCA	principal component analysis
PET	positron emission tomography
PSSM	position-specific scoring matrix
ROI	regions-of-interesting
SDPN	stacked deep polynomial network
SNA	social network analysis
SPD	structural patch decomposition
STM	structural topic modeling
STS	soft-tissue sarcoma
SVM	support vector machine
TF-IDF	term frequency-inverse document frequencies
WoS	Web of Science

personalization. Thus, it is promising for improving individuals' and communities' health and well-being. The rise of smart healthcare activates a dramatic increase in data regarding health and illnesses from diverse communication and information devices and technologies. This multi-source data presents enormous opportunities to augment medical knowledge, clinical care, and patient experience (Dautov et al., 2019). Scholars have been developing effective resolutions for collecting, transferring, storing, aggregating, and analyzing multi-source data, which is known as information fusion, to manage the unprecedented amount of data effectively and efficiently. Information fusion combines information from multiple data sources to enable precise and comprehensive descriptions compared to individual data sources (Haghighat et al., 2016). Automatic information fusion is essential, particularly in smart healthcare, where large volumes of data from diverse spatially distributed locations should be fused in real-time. As Xie et al. (2020) suggest, information dissemination, sharing, and integration among multiple data sources are significant in smart healthcare. Sendra et al. (2018) also demonstrate that the combination of information and communication technologies, AI, and smart devices contribute to reducing costs for smart healthcare (Sendra et al., 2018). Thus, many multimodal AI information fusion frameworks and models are available recently. For instance, Khan et al. (2021) proposed and demonstrated the effectiveness of a multimodal deep learning information fusion approach for segmenting and classifying skin lesions. Ali et al. (2020) proposed an intelligent healthcare system using deep learning and feature fusion methodologies to predict heart diseases. The close study of information fusion for healthcare with AI is becoming a crucial and active field of research. Interest in facilitating the development of smart health through information fusion based on AI technologies is continually increasing within academia, amongst medical and healthcare institutions, and in relevant government sectors. Reviews have been carried out on individual relevant topics, such as information fusion, smart health, and AI, most of which used synthesis or systematic methodologies based on small samples. No study has provided an overview of the target field that considers information fusion, healthcare, and AI simultaneously. Due to the significance of this interdisciplinary research field, it is necessary to understand its issues and trends to further promote its future development. By using structural topic modeling (STM) and bibliometrics, this study aims to thoroughly elucidate extant academic output related to information fusion for healthcare with AI globally.

1.1. Information fusion for healthcare with AI

Fusion constitutes "the process of joining two or more things together to form a single entity" (Jouirou et al., 2019, p. 309). Information fusion, as a popular technology adopted in various areas, for example, AI, robotics, image processing, and wireless sensors, refers to the integration of multiple sources of information for obtaining more reliable, consistent, and accurate information to support optimal decision-making. To facilitate such decision-making, the inference seems to be critical for combining and transforming data from multiple sources into a discrete and actionable format for subsequent analysis. In various real-world applications, information fusion has demonstrated effectiveness for inference and decision-making support that is impossible by using a single sensor/source. In computer science, information fusion concerns integrating complementary information without consideration of the number or types of sources. Generally, the common aim of information fusion is to enhance accuracy and decrease uncertainty by exploring and integrating complementary information.

AI, with its remarkable advances in pattern recognition and natural language processing, has facilitated massive multi-source data processing and leveraged referencing power due to the rapid identification of more accurate and targeted patterns. Recently, AI techniques, particularly those derived from deep learning algorithms, are successfully adopted to resolve a variety of issues concerning information fusion, mainly related to medical and health, e.g., automatic electroencephalography (EEG) classification (Ieracitano et al., 2020), diagnosis of infectious diseases (Javed et al., 2020), medical image segmentation (Feng et al., 2020), and medical image classification (Hu et al., 2022). The core of smart health is predictive, preventive, personalized, and participatory medicine that aims at realizing evidence-based healthcare and medical systems. Information fusion is claimed to have the potential to facilitate smart health, particularly with advances in AI that makes data and knowledge super-accessible.

Recognizing the increasing importance of the research field of information fusion for healthcare with AI, as witnessed by the continuingly growing research interest and scientific output (see Fig. 4), it is essential to present a summarized view of the extant literature. However, such studies are rare, with only reviews found to superficially address one or two aspects of the research target, for example, information fusion technologies (e.g., Liu, Zhou, Hu, & Wu, 2018; Snidaro et al., 2015; Slanzi et al., 2017), information fusion for image classification (e.g., Imani & Ghassemian, 2020), information fusion for decision-making (e.g., Xu & Zhao, 2016), or information fusion in visual question-answering (Zhang et al., 2019). Furthermore, existing reviews commonly adopted qualitative approaches using small samples, such as synthesis or systematic analysis methodologies. In addition, those reviews usually focused on analyzing specific issues and failed to offer a quantitative overview of the field of information fusion for healthcare with AI. Regarding the current outbreak of COVID-19, discussion on theories, technologies, and potential breakthroughs relying on information fusion for smart health with AI advances have become more significant and necessary. Consequently, certain questions, such as "what are the prominent research topics in this interdisciplinary field" and "what might be the future of research on the realization of smart health systems and services based on AI technologies using collective and fused information from multi-sources" have become particularly important.

1.2. Structural topic modeling and bibliometrics

The rapidly increasing number of academic articles and dramatic development of computational power have revived the century-old approach of bibliometric analysis to discover major topics and frontiers in active interdisciplinary disciplines. In a general sense, bibliometrics refers to the study or measure of texts and information from a quantitative perspective. However, the traditional bibliometric analysis focuses primarily on structured metadata (e.g., year of publication, source, or citation index) rather than textual information, which constrains its capability to deal with diverse types of data.

Traditional methods, such as keyword co-occurrence analysis and keyword frequency analysis, are commonly applied in research topic detection. Compared to these methods, topic models offer increased flexibility, rely less on domain experts (Kuhn, 2018), and are appropriate for the content analysis of a large volume of data (Nielsen & Börjeson, 2019). Particularly, STM (Roberts et al., 2014a; 2014b) has recently received growing attention in literature analysis.

Bibliometrics and topic models are significantly valuable for depicting a general landscape of and extracting semantically meaningful topics from large-scale textual data. Indeed, researchers have applied bibliometrics and topic models to provide general overviews of specific research fields, particularly interdisciplinary research areas (e.g., Chen et al., 2020c; Zhang et al., 2020a) and are objective, reliable, and cost-effective (Campbell et al., 2010).

By utilizing the advantages of STM and bibliometrics, this study jointly adopted the two methods to analyze a broad range of unstructured text data. By further applying a non-parametric Mann-Kendall (MK) trend test, a clustering analysis, and a topic distribution visualization technique, we proposed to systematically elucidate the research status and tendencies of this specific scientific area.

1.3. Research aims and questions

With the increasingly diverse topics and technologies in research concerning information fusion for healthcare with AI, quantitative analysis for a better understanding of the following research questions (RQs) is timely:

RQ1: What are the publication trends, top studies, journals, countries/regions, institutions, and authors ranked by article count?
RQ2: What are the prominent topics that are discussed in research concerning information fusion for healthcare with AI?
RQ3: How do the identified prominent topics change in research popularity over time?
RQ4: How do the topic distributions vary across top journals, countries/regions, and institutions ranked by article count?
RQ5: What are the scientific co-authorship among countries/regions, institutions, and authors in each topic?

These research questions are developed by referring to previous bibliometric studies that, similar to this study, aim to understand the research landscape of a field. Examples include AI-enhanced human electroencephalogram analysis (Chen et al., 2021a) and educational technologies (Chen et al., 2020c). According to the previous literature, by answering these questions, we can offer a state-of-the-art understanding of research about information fusion for healthcare with AI and provide valuable implications to scholars and project investigators for its future development.

More specific motivations for answering each of these questions are illustrated as follows. First, by answering RQ1, researchers can 1) understand the international scientific progress and the field's development tendencies , 2) exploit the outcomes of influential literature (Hao et al., 2020), 3) recognize suitable sources to share and publish literature on information fusion for healthcare with AI

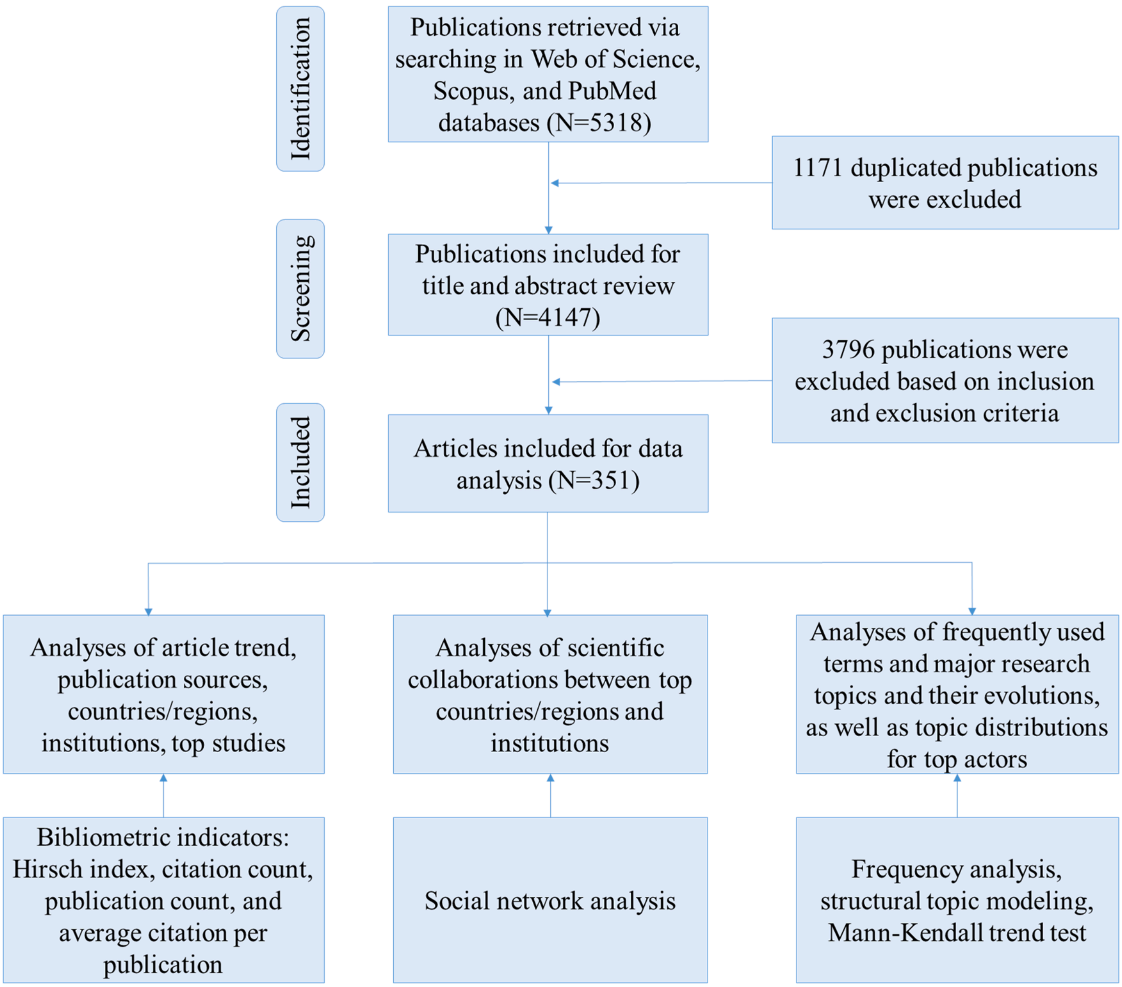


Fig. 1. Analytical framework.

(Song et al., 2019), and 4) be aware of essential actors to learn from . Second, answers to RQ2 will help grasp the past and current academic landscape of research on information fusion for healthcare with AI and keep scholars informed of crucial issues that need attention (Chen et al., 2021a). Answers to RQ3 help understand the developmental tendencies of research topics and offer insights into the future of this field. These findings allow researchers, policy-makers, and practitioners to be aware of research frontiers when taking scientific/technological actions (Hao et al., 2020; Song et al., 2019). Answers to RQ4 help understand influential countries/regions, institutions, and authors in the whole field and specific research direction(s) of information fusion for healthcare with AI (Chen et al., 2022). Answers to RQ5 help understand the cooperative patterns/relationships and recognize potential academic partners.

To answer the above questions, this study jointly applied STM, the non-parametric MK trend test, clustering analysis, and bibliometrics to quantitatively probe the academic literature concerning information fusion for healthcare with AI. Specifically, we adopted STM to profile primary topics from 351 relevant articles and the MK test to investigate annual topic trends in prevalence. We then employed clustering analysis to reveal topical relationships and compared the topic distributions of different top contributors via visualization. We also identified top studies in the field by using citation-based indicators. Subsequently, we investigated collaborative patterns among countries/regions, institutions, and authors based on social network analysis.

2. Data and methods

The analytical framework of the current study is presented in Fig. 1, comprising data collection and pre-processing, topic modeling, and performance analysis.

2.1. Data collection and pre-processing

Literature data regarding information fusion for healthcare with AI were gathered from Web of Science (WoS), PubMed, and Scopus databases. WoS has long been recognized as a quality-ensured source for the scientific evaluation of specific research fields Zhang et al., 2019b; Zhang, Chen, & Zhu, 2016). PubMed, a globally recognized medical literature database, has comprehensive coverage of literature on life sciences and biomedicine. Scopus is a reliable (Adriaanse & Rensleigh, 2013) and comprehensive (Mongeon & Paul-Hus, 2016) scientific source of peer-reviewed literature.

In the WoS, "TS," suggesting the title, abstract, or keyword of an article, was used. Journal articles categorized in medical/health-related subjects, written in English, and indexed in Science Citation Index Expanded, Social Sciences Citation Index, Arts & Humanities Citation Index, and Emerging Sources Citation Index, were included. In PubMed, we adopted [Title/Abstract] as a search field, and articles written in English were included. In Scopus, we adopted "TITLE-ABS-KEY" as a search field. Journal articles categorized in medical/health-related subjects and written in English were considered. The search terms were determined based on the use of a Delphi method. Two experts were first asked to write down any keywords associated with AI, information fusion, and medical/health. Next, the experts refined their earlier answers based on the verification of the keywords' relevance to the research areas and in light of each other's responses. The final list of search terms can be seen in Table S1 in the Appendix, comprising three sets, including AI-related keywords, keywords related to information fusion, and medical/health-related keywords. The retrieval was conducted in 2020.

Through the data search, 420, 3165, and 1733 articles with complete bibliographic information were collected from WoS, PubMed, and Scopus, respectively. A total of 1171 duplicated records were deleted based on the examination of title, journal, year of publication, and author information. The remaining 4147 articles were manually screened for relevance to our research target. The screening was performed by domain experts with a deep understanding and knowledge of this interdisciplinary field with the guidance of the criteria given in Table 1. When judging an article's relevance to the research target, we looked at the first exclusion criterion (i.e., biochemical related (genetic)). When it met this exclusion criterion, we excluded it immediately with no further evaluation; otherwise, we continued to check its relevance to biometric authentication (the second exclusion criterion). An article might match more than one exclusive criterion. However, we excluded it to facilitate screening when it matched any of the exclusive criteria. Following such a hierarchical method of data screening, the two experts each screened the same 300 articles, resulting in inter-rater reliability of 93%. The remaining articles were separated into two sets, each of which was screened by one expert. Totally, 351 articles were chosen. It is worth noting that many articles focused on AI techniques for information fusion but were unrelated to the topic of health. In addition, many of the excluded articles mentioned issues concerning information fusion or AI techniques only as a potential direction for future research.

Pre-processing was performed based on a Natural Language Toolkit[1]. Specifically, tokenization (Manning & Schutze, 1999) and word normalization were employed to split titles/abstracts into words and transform capital letters into lowercases, respectively. Numbers, punctuations, symbols, and stop-words were excluded since they were "insufficiently specific to represent document content" (Salton, 1991, p. 967). Term frequency-inverse document frequencies (TF-IDF) technology was utilized to eliminate unimportant words by empirically setting a TF-IDF threshold of 0.03.

2.2. Structural topic modeling

To understand the predominant research topics in the field of information fusion for healthcare with AI, in addition to identifying

[1] https://www.nltk.org/

Table 1
Inclusion and exclusion criteria.

Inclusive criteria	AI-based approaches	
	IA1	Traditional machine learning approaches
	IA2	Deep learning approaches
	IA3	Reasoning and metrics
	Information fusion	
	II1	Multi-source information fusion (different knowledge domains)
	II2	Multimodality information fusion (different knowledge domains)
	II3	Fusion mechanisms
	Medical/Health-related topics	
	IT1	Solutions for smart health (predictive, preventive, personalized, and participatory)
	IT2	Medical/Clinical image processing and application
	IT3	Medical/Clinical signal processing and application
	IT4	Medical/Clinical natural language processing and application
	IT5	Medical/Clinical integrated processing and application
	IT6	Generic processing and application for health/medical purposes
	IT7	Human activity detection and assessment for health/medical purposes
	IT8	Safety (food security, fall prevention)
Exclusive criteria		Biochemical related (genetic)
		Biometric authentication
		Emotion recognition not for health purposes
		Gesture, motion, movement recognition not for health purposes
		Computer-aided detection/diagnosis without AI
		Pharmacology
		Food and agriculture-relevant research
		Robotic navigation/localization
		Underwater acoustic target recognition
		Wireless sensor application not for health purposes
		Research on chemical/biological/surgery fusion mechanisms

the frequently used terms/phrases/keywords in the analyzed articles, we also adopted topic models to mine the semantic, intellectual structures, and latent topics hidden within the literature. Although keyword analysis methodologies are broadly adopted to identify critical issues in a field of research, there are problems. Specifically, many articles do not include keywords; some articles include keywords selected from the list offered by journals. As a result, sometimes, the keywords displayed in an article are not the best summarization (Chen et al., 2022). To address the above problems, this study further performed advanced topic modeling and analysis. Researchers have widely agreed that, in topic detection/tracking, topic models are more adaptable and efficient in affording comprehensive content analyses compared to terms/phrases/keywords analysis (Jiang et al., 2016; Kuhn, 2018).

The topic model is an instrument for uncovering important topics from large-scale textual data (McFarland et al., 2013; Nichols, 2014). In the topic model, an assumption exists that each document consists of a set of hidden topics based on probability distributions, with each term in the document being selected based on probability distributions from the vocabulary of the topics. When using topic models, model parameters, such as the probability of each document being allocated to each topic, are determined based on Bayesian inferences. In this study, STM, as a popular topic model, was used to detect general themes of the 351 articles concerning information fusion for healthcare with AI.

Fig. 2 presents a diagram of the STM. The unshaded nodes represent hidden variables, and the shaded ones are observed variables. The rectangles represent replication: $n \in \{1, 2, \ldots, N\}$ donates terms covering a document; $k \in \{1, 2, \ldots, K\}$ represents each of the K topics; and $d \in \{1, 2, \ldots, D\}$ denotes the document number. The aim of STM is to estimate and output θ and β, representing document-topic and topic-word distributions, respectively, based on the observed terms W.

In STM, θ_d represents the hidden per-document topic proportions, and $\beta_{d,k,v}$ represents the per-corpus topic-term distributions; $z_{d,n}$ represents the underlying topic allocation of each term, and $w_{d,n}$ represents the term selected from terms indexed by $v \in \{1,2, \ldots, V\}$. STM assumes that the generation of each document d follows two steps:

Step 1. Select a distribution over topics θ_d for d in a random manner.
Step 2. For each term w_n in d:

(a) Select a topic $z_{d,n}$ from the distribution over topics θ_d in Step 1 in a random manner.
(b) Select a term w_n from the corresponding distribution over $\beta_{d,k,v}$ in a random manner, in which $k = z_{d,n}$.

The STM was constructed using an R package *stm* (Roberts et al., 2014a). A multiple modeling strategy was performed to determine a suitable K. Semantic coherence and exclusivity were adopted for model comparison and evaluation. A high semantic coherence indicates that more possible terms associated with a topic appear in the same document, and a high exclusivity indicates that more terms exclusively belong to a single topic. The model was finalized by manually examining candidates.

First, the candidate models with K ranging from five to 20 were constructed and compared according to their semantic coherence and exclusivity (see Fig. 3). The model with K = 14 topics (i.e., 14-topic model) exhibited better performance regarding semantic coherence and exclusivity. Additionally, domain experts identified the 14-topics model as the optimal one by manually comparing it

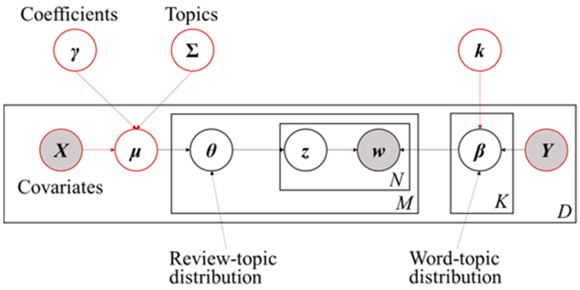


Fig. 2. A diagram of STM.

with estimations with fewer and more topics (e.g., K = 13 and K = 15) (see Table 2) based on the criteria listed in Chen et al. (2020c). Generally, when using fewer topics, essential issues were missed, while the use of more than 14 topics caused a single issue to be repeatedly identified. For instance, in the 13-topic model, *functional magnetic resonance imaging*, as an essential issue in the research field, did not appear, whereas in the 15-topic model, *wavelet-based statistical analysis*, similar to *statistical inference and models for multimodality data fusion*, appeared. Through comparisons, we selected the 14-topic model since it contained all crucial issues in the research field. Labels for each of the 14 topics were determined based on representative terms and documents. The frequent and exclusive terms (FREX) metric in a topic indicates that terms are highly represented (Airoldi & Bischof, 2016). The FREX considers a term's possibility and exclusivity associated with a topic based on the computation of the harmonic mean of the ranks of its possibility and exclusivity, respectively.

Based on the estimated topic-document distribution matrix θ, a topic can be calculated by summing up θ_{ij}, in which θ_{ij} ($i = 1, 2, \ldots 351$, $j = 1, 2, \ldots 14$) represents the possibility of document i associated with topic j. Additionally, based on the topic proportion matrices of major contributors in json formats, this study implemented a Cluster Purity Visualizer[2] to draw a distribution graph, which was further modified by JavaScript packages d3.v3.js[3] and ClusterPurityVisualizer.js[4] to adjust layout and color.

2.3. Mann-Kendall trend test

With the estimated STM parameters, we computed the proportion of each topic using Eq. (1) to indicate their prevalence in the corpus:

$$\mathrm{P_k} = \frac{\sum_{\mathrm{d}} \theta_{\mathrm{d,k}}}{\mathrm{D}} \tag{1}$$

In the equation, $\mathrm{P_k}$ represents the $\mathrm{k_{th}}$ topic proportion, $\theta_{\mathrm{d,k}}$ is the $\mathrm{k_{th}}$ topic proportion in the $\mathrm{d_{th}}$ document, and D is 351. We computed the $\mathrm{k_{th}}$ topic proportion in year t with the use of Eq. (2) to conduct a trend analysis:

$$\mathrm{P_{k,t}} = \frac{\sum_{\mathrm{d|Y=t}} \theta_{\mathrm{d,k}}}{\mathrm{D_t}} \tag{2}$$

In the equation, $\mathrm{Y_d}$ donates the year when the $\mathrm{d_{th}}$ document was published; and $\mathrm{D_t}$ is the number of documents that were published in year t. We used a Mann-Kendall (MK) test (Mann, 1945) to examine the developmental tendency of each topic. The MK is a non-parametric test to understand the developmental tendencies in time series. Instead of assuming a normal distribution, MK is flexible to outliers by assuming a null hypothesis of no trend and an alternative hypothesis of trends in increase or decrease.

Given a time series $\mathrm{X_i} = \mathrm{x_1, x_2, \ldots, x_n}$, the test statistic S is determined by Eq. (3):

$$\mathrm{S} = \sum_{\mathrm{i=1}}^{\mathrm{n-1}} \sum_{\mathrm{j=i+1}}^{\mathrm{n}} \mathrm{sign}\left(\mathrm{x_j} - \mathrm{x_i}\right) \tag{3}$$

$$\mathrm{sign}\left(\mathrm{x_j} - \mathrm{x_i}\right) = \left\{ \begin{matrix} -1 \mathit{if}\left(\mathrm{x_j} - \mathrm{x_i}\right)\langle 0 \\ 0 \mathit{if}\left(\mathrm{x_j} - \mathrm{x_i}\right) = 0 \\ 1 \mathit{if}\left(\mathrm{x_j} - \mathrm{x_i}\right)\rangle 0 \end{matrix} \right. \tag{4}$$

In the equation, n represents data point numbers, $\mathrm{x_i}$ and $\mathrm{x_j}$ represent values in times i and j (j > i), separately, and $\mathrm{sign}(\mathrm{x_j} - \mathrm{x_i})$ represents the sign function given by Eq. (4). S is a normal distribution with E(S) and variance V(S) expressed as Eqs. (5) and (6), respectively:

[2] https://gist.github.com/nswamy14/e28ec2c438e9e8bd302f
[3] https://gist.github.com/dselivanov/21c4c992217e08128cb2ca7854e320ae
[4] https://gist.github.com/nswamy14/e28ec2c438e9e8bd302f

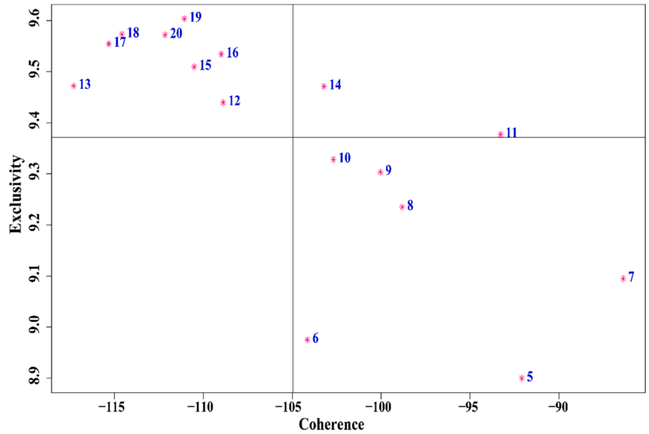


Fig. 3. Model diagnostics for STM.

Table 2
Comparisons of the 13-, 14-, and 15-topic models.

Labels for the 13-topic model	Labels for the 14-topic model	Labels for the 15-topic model
multimodality feature learning and representation for intelligent health and medical systems	multimodality feature learning and representation for intelligent health and medical systems	multimodality feature learning and representation for intelligent health and medical systems
magnetic resonance imaging and computed tomography data processing	magnetic resonance imaging and computed tomography data processing	magnetic resonance imaging and computed tomography data processing
prediction and computer-aided prognosis based on multimodal biomedical data	prediction and computer-aided prognosis based on multimodal biomedical data	prediction and computer-aided prognosis based on multimodal biomedical data
convolutional neural networks and transfer learning for multi-scale and multi-tasks	convolutional neural networks and transfer learning for multi-scale and multi-tasks	convolutional neural networks and transfer learning for multi-scale and multi-tasks
multimodality medical image fusion and fuzzy-based intelligent health and medical systems	multimodality medical image fusion and fuzzy-based intelligent health and medical systems	multimodality medical image fusion and fuzzy-based intelligent health and medical systems
smart devices, sensors, and infrastructure for intelligent health and medical systems	smart devices, sensors, and infrastructure for intelligent health and medical systems	smart devices, sensors, and infrastructure for intelligent health and medical systems
machine learning for biomedical and genomic data fusion	machine learning for biomedical and genomic data fusion	machine learning for biomedical and genomic data fusion
human activity, disease, and mental state detection based on multimodality data	human activity, disease, and mental state detection based on multimodality data	human activity, disease, and mental state detection based on multimodality data
multi-atlas label fusion and segmentation	multi-atlas label fusion and segmentation	multi-atlas label fusion and segmentation
multimodal fusion for brain images	multimodal fusion for brain images	multimodal fusion for brain images
statistical inference and models for multimodality data fusion	statistical inference and models for multimodality data fusion	statistical inference and models for multimodality data fusion
electroencephalogram analysis	electroencephalogram analysis	electroencephalogram analysis
electrocardiogram analysis	electrocardiogram analysis	electrocardiogram analysis
	electroencephalogram and functional magnetic resonance imaging integration	electroencephalogram and functional magnetic resonance imaging integration
		wavelet-based statistical analysis

$$\mathrm{E(S)} = 0 \tag{5}$$

$$\mathrm{V(S)} = \frac{\mathrm{n(n-1)(2n+5)}}{18} \tag{6}$$

Z is represented by Equation (7):

$$\mathrm{Z} = \begin{cases} \dfrac{\mathrm{S}-1}{\sqrt{\mathrm{V(S)}}} if S > 0 \\ 0 if S = 0 \\ \dfrac{\mathrm{S}+1}{\sqrt{\mathrm{V(S)}}} if S < 0 \end{cases} \tag{7}$$

A positive/negative Z reflects an increasing/decreasing trend. Given a confidence level α, a significant tendency is detected when $|\mathrm{Z}| > \mathrm{Z}(1-\alpha/2)$, in which $\mathrm{Z}(1-\alpha/2)$ represents the corresponding value of $\mathrm{p} = \alpha/2$.

2.4. Clustering analysis

We further conducted a clustering analysis of the 14 labeled topics based on a document-topic distribution matrix for topic correlation exploration. In this step, no domain expert is involved. We used a hierarchical clustering approach with a complete-linkage agglomerative approach (Sneath & Sokal, 1973), which defines that the distance between two clusters refers to the maximum distance between their individual components. The document-level similarity was calculated based on cosine similarity. For vectors A and B, $\cos(\mathrm{A},\ \mathrm{B})$ is given by Eq. (8):

$$\text{similarity} = \cos(\mathrm{A},\mathrm{B}) = \frac{\mathrm{A}\cdot\mathrm{B}}{||\mathrm{A}||||\mathrm{B}||} = \frac{\sum \mathrm{A_i}\times\mathrm{B_i}}{\sqrt{\sum(\mathrm{A_i})^2}\times\sqrt{\sum(\mathrm{B_i})^2}} \tag{8}$$

2.5. Social network analysis and performance analysis

Social network analysis (SNA) aims to reveal relations among entities and has been broadly adopted in a variety of areas for predicting structures of relations and structure influences (Chen et al., 2020a). In the present study, the SNA was conducted by Gephi (Bastian et al., 2009) to visualize the relations between countries/regions, institutions, or authors by considering countries/regions, institutions, or authors as entities. In a collaborative network of institutions, each node denotes an institution with its size being proportional to its productivity. The link weight between two nodes indicates the degree of collaboration.

Performance analysis is frequently used in bibliometrics to measure the scientific outputs of researchers. The Hirsch index (H-index) has received significant attention in the scientific community (Hirsch, 2005) by combining measures of scientific production and impact. The H-index is now commonly employed to evaluate the scientific influence of a country, an institution, an author, and a publication source. This study also adopted other frequently used bibliometric indicators: article count, citation count, and average citations per article (ACP). The total number of articles published by a country/region, an institution, an author, and a publication source focus on the count of their articles. The number of citations associated with an article indicates its impact on the scientific community. Therefore, citation count can also evaluate academic impact.

3. Results

3.1. Publication trend

The annual distribution of articles is shown in Fig. 4. In general, studies concerning information fusion for healthcare with AI experienced significant growth in annual numbers, especially since 2010. The number rose from one in 1998 to 62 in 2020. The polynomial regression results were also integrated, from which an exponential growth tendency suggested significant growth in interest in the field. The trend analysis demonstrates the continuing importance and impact of research focusing on information fusion for healthcare with AI in academia.

3.2. Top studies

According to citation count and annual citations (C/Y) (Chen et al., 2022), the top 10 studies within the 351 articles concerning information fusion for healthcare with AI are presented in Table 3. Six studies appear in both ranking lists (i.e., Ordóñez & Roggen, 2016; Wang et al., 2012; Setio et al., 2016; Suk et al., 2014; Vallières et al., 2015; Liu et al., 2014). Moreover, calculated by either total citations or C/Y, the study conducted by Ordóñez and Roggen (2016) took the first place, and thus the research significance of the work

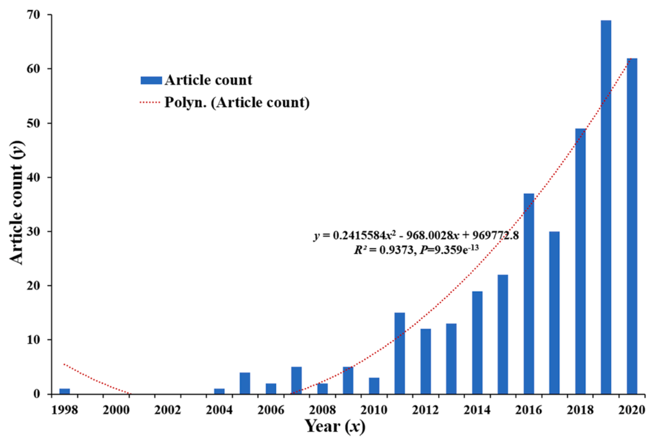


Fig. 4. Trend analysis of article count.

Table 3
Top studies ranked by total citations and annual citations.

Studies	Title	C
Ordóñez and Roggen (2016)	"deep convolutional and LSTM recurrent neural networks for multimodal wearable activity recognition"	1065
Wang et al. (2012)	"multi-atlas segmentation with joint label fusion"	669
Setio et al. (2016)	"pulmonary nodule detection in CT images: false positive reduction using multi-view convolutional networks"	633
Suk et al. (2014)	"hierarchical feature representation and multimodal fusion with deep learning for AD/MCI diagnosis"	485
Vallières et al. (2015)	"a radiomics model from joint FDG-PET and MRI texture features for the prediction of lung metastases in soft-tissue sarcomas of the extremities"	448
Liu et al. (2014)	"multimodal neuroimaging feature learning with multimodal stacked deep polynomial networks for diagnosis of Alzheimer's disease"	259
Liu, Zhou, Yuan, & Chen, 2012	"automatic seizure detection using wavelet transform and SVM in long-term intracranial EEG"	205
Groves et al. (2011)	"linked independent component analysis for multimodal data fusion"	195
De Bie et al. (2007)	"kernel-based data fusion for gene prioritization"	180
Rohe and Noppeney (2015)	"cortical hierarchies perform Bayesian causal inference in multisensory perception"	159
Studies	Title	C/Y
Ordóñez and Roggen (2016)	"deep convolutional and LSTM recurrent neural networks for multimodal wearable activity recognition"	213.00
Setio et al. (2016)	"pulmonary nodule detection in CT images: false positive reduction using multi-view convolutional networks"	126.60
Wang et al. (2012)	"multi-atlas segmentation with joint label fusion"	83.63
Vallières et al. (2015)	"a radiomics model from joint FDG-PET and MRI texture features for the prediction of lung metastases in soft-tissue sarcomas of the extremities"	74.67
Suk et al. (2014)	"hierarchical feature representation and multimodal fusion with deep learning for AD/MCI diagnosis"	69.29
Shi et al. (2017)	"multimodal neuroimaging feature learning with multimodal stacked deep polynomial networks for diagnosis of Alzheimer's disease"	51.67
Liu et al. (2014)	"multimodal neuroimaging feature learning for multiclass diagnosis of Alzheimer's disease"	43.17
Hu et al. (2018)	"weakly-supervised convolutional neural networks for multimodal image registration"	37.33
Cheng et al. (2018)	"deep similarity learning for multimodal medical images"	33.00
Nie et al. (2018)	"3-d fully convolutional networks for multimodal Isointense infant brain image segmentation"	28.50

Note: C: citation count; C/Y: annual citations.

was self-evident. Specifically, by using convolutional and long short-term memory (LSTM) recurrent units, Ordóñez and Roggen proposed an innovative generic deep framework to recognize multimodal wearable activities with the following features: (1) applied to multimodal wearable sensors; (2) could naturally conduct sensor fusion; (3) did not require expert knowledge in feature design; and (4) clearly modeled temporal dynamics of feature activations. Experiments suggested the framework's effectiveness in gesture recognition. Their study highlighted that the LSTM-based framework was able to learn temporal feature activation dynamics and claimed that the framework had the potential to fuse multimodal sensors for fusion performance improvement.

Wang et al. (2012) proposed a label fusion strategy to segment multi-atlases by considering atlas dependency and directly reducing label error. Specifically, weighted voting was conducted by minimizing the overall expected label error and explicitly modeling the "pairwise dependency between atlases as the joint likelihood of two atlases that made a segmentation error at a voxel" (p. 611). The likelihood was estimated using intensity similarity between atlas pairs and the targeted image near each voxel. Experimental results demonstrated consistent and significant improvement of the proposed strategy over other methods by assigning atlas weights individually to deal with magnetic resonance image (MRI) segmentation.

Setio et al. (2016) developed a computer-assisted pulmonary nodule detection system based on multi-view convolutional networks (ConvNets) to learn discriminative features from the training set in an automated manner. The network was filled with nodule candidates acquired through a combination of detectors for solid, sub-solid, and large nodules. The proposed system consisted of multi-streams of two-dimensional (2-D) ConvNets, for which the outputs were integrated by utilizing a dedicated fusion approach. Through evaluation, the proposed system demonstrated promising potential to assist decision-making in lung cancer screening with high detection sensitivities and low computation time.

Suk et al. (2014) developed an approach to represent high-level latent and shared features from neuroimaging modalities based on deep neural networks. Specifically, the deep Boltzmann machine was used for finding "a latent feature representation from a volumetric patch and the joint feature representation from multimodality" (p. 579). Experiments indicated that the proposed approach was promising in dealing with binary classification tasks by learning high-level features based on deep learning to detect complicated hidden patterns in MRI and positron emission tomography (PET) in an efficient and hierarchical manner.

Vallières et al. (2015) designed a joint fluoro-D-glucose (FDG)-PET and MRI texture-driven approach to evaluate lung metastasis risk in soft-tissue sarcomas (STSs) at an early stage. Vallières et al. constructed tumor outcome prediction models based on various radiomics features, texture extraction, and multivariable modeling methodologies. Experiments indicated that the FDG-PET and MRI texture features were highly valuable as prognostic STSs factors to offer insights into underlying biology. Moreover, compared to MRI texture features, FDG-PET texture features were more valuable for lung metastasis prediction in STS cancer. However, prediction performance could be further improved by adding supplementary MRI information to FDG-PET through fusion.

Liu et al. (2014) proposed an innovative Alzheimer's disease diagnosis framework using deep learning along with a zero-masking data fusion strategy to obtain complementary information from multimodalities. The framework could identify Alzheimer's disease progression in different stages with minimal clinical prior knowledge. Compared to advanced support vector machine (SVM)-driven approaches and other deep learning technologies, the proposed framework was able to fuse multimodal neuroimaging features with less labeled data.

Liu, Zhou, Yuan, & Chen, 2012 reported the superiority of an algorithm in detecting seizures using discrete wavelet transform (DWT) and SVMs based on long-term intracranial EEG signals. Specifically, DWT was adopted in nonstationary processes as a powerful time-frequency tool. At the same time, SVM showed superiority in addressing pattern recognition with small samples and those of nonlinear and high dimensions.

Groves et al. (2011) proposed a "Linked ICA" method that automatically determined the best weighting of each modality and detected single-modality structured elements, and could be used for tensor independent component analysis (ICA), spatially concatenated ICA, or their combinations simultaneously. Linked ICA was a promising tool that could be used in any scenario in which multimodalities were obtained across a single shared dimension.

De Bie et al. (2007) proposed a kernel approach for gene prioritization with three unique features: (1) good performance guaranteed by the original kernel approach; (2) uniform linear integration of different kernel matrices that were robust and effective for data fusion; and (3) robustness against unrelated or extremely noisy data sources ensured by data-dependent automated weighting processes.

With psychophysics, Bayesian models, functional MRI (fMRI), and multivariate decoding in audio-visual spatial localization tasks, Rohe and Noppeney (2015) demonstrated Bayesian causal inference through hierarchical multi-sensory processes in the human brain.

Shi et al. (2017) developed a multimodal stacked deep polynomial network (MM-SDPN) approach for Alzheimer's disease diagnosis by fusing and learning representations of features based on multimodal neuroimages. SDPNs learned high-level features from MRI and PET to be fed to another SDPN for multimodal neuroimaging data fusion. Experiments indicated that MM-SDPN was a powerful tool for representing multimodal neuroimaging biomarkers with effectiveness in Alzheimer's disease diagnosis in binary/multiclass classification tasks.

Hu et al. (2018) designed a flexible registration method to integrate various "neural network algorithms, deformation regularizers, and anatomical features with various sizes, shapes, and availabilities" (p. 1). The end-to-end convolutional neural networks (CNNs) aimed at predicting displacement areas to align multi-labeled structures for specific image pairs while training, with only unlabeled image pairs being inputted.

Cheng et al. (2018) developed a deep similarity learning method by training a binary classifier to learn the correspondences of two image patches. Specifically, they used the corresponding states of patch pairs to formulate a classification scenario and trained a deep neural network (DNN) through supervised learning. They also proposed to utilize a multimodal stacked denoising auto-encoder to conduct effective pre-training of the DNN.

To resolve the challenge of extremely low tissue contrast in tissue segmentation, Nie et al. (2018) presented a three-dimensional (3-D) multimodal fully convolutional network (FCN) to segment isointense phase brain MRIs. Specifically, they "extended the conventional FCN from 2-D to 3-D, and then intuitively integrated coarse (naturally high-resolution) and dense (highly semantic) feature maps to better model tiny tissue regions" (p. 1123). Transformation and fusion modules were also used to connect the aggregated layers and to serve feature map fusion, respectively. Experimental results demonstrated that: (1) a careful combination of coarse and dense feature maps could significantly enhance segmentation; (2) batch normalization could facilitate network convergence, particularly with the occurrence of hierarchical feature aggregations; and (3) the integration of multimodal information could improve segmentation.

3.3. Publication source analysis

A total of 132 publication sources were found. The top 13 ranked by article count are presented in Table 4. IEEE Engineering in Medicine and Biology Society and IEEE Journal of Biomedical and Health Informatics were the most prolific, with 25 and 18 articles, respectively. Looking at H-index, the top sources were IEEE Engineering in Medicine and Biology Society (H-index value of 13),

Table 4
Top productive publication sources.

Publication sources	A (R)	H (R)	C (R)	ACP
IEEE Engineering in Medicine and Biology Society	25 (1)	13 (1)	393 (9)	15.72
IEEE Journal of Biomedical and Health Informatics	18 (2)	10 (3)	447 (8)	24.83
Journal of Medical Imaging and Health Informatics	15 (3)	5 (10)	50 (38)	3.33
Medical Image Analysis	15 (3)	12 (2)	799 (3)	53.27
Computer Methods and Programs in Biomedicine	12 (5)	6 (7)	154 (22)	12.83
Sensors (Basel, Switzerland)	12 (5)	6 (7)	1282 (1)	106.83
IEEE Transactions on Biomedical Engineering	9 (7)	8 (4)	722 (5)	80.22
IEEE Transactions on Medical Imaging	8 (8)	7 (5)	792 (4)	99.00
Medical Image Computing and Computer-Assisted Intervention	8 (8)	7 (5)	99 (25)	12.38
Computerized Medical Imaging and Graphics	7 (10)	6 (7)	271 (11)	38.71
Computers in Biology and Medicine	7 (10)	5 (10)	80 (30)	11.43
International Journal for Computer Assisted Radiology and Surgery	7 (10)	2 (25)	41 (47)	5.86
Physics in Medicine and Biology	7 (10)	5 (10)	536 (7)	76.57

Abbreviations: R: ranking position; H: H-index; A: article count; C: citation count; ACP: average citations per article.

Medical Image Analysis (12), and IEEE Journal of Biomedical and Health Informatics (10). Concerning ACP, the top three were Sensors (Basel, Switzerland) (ACP value of 106.83), IEEE Transactions on Medical Imaging (99), and IEEE Transactions on Biomedical Engineering (80.22).

3.4. Top countries/regions, institutions, and authors

A total of 43 countries/regions have contributed to research concerning information fusion for healthcare with AI. The top 12 ranked by article count are given in Table 5. China, the USA, and the UK were at the top among the lists ranked based on article count, H-index, and citation count, reflecting their importance in the research. Concerning ACP, the top three were the UK (ACP value of 96), Germany (80.55), and Canada (75).

There were 502 institutions that have contributed to research concerning information fusion for healthcare with AI. Table 6 presents the top 12 productive institutions, with five from China and four from the USA. In terms of productivity and influence measured by article count and H-index, the top three were the University of North Carolina at Chapel Hill, the Chinese Academy of Sciences, and the University of Pennsylvania. Regarding ACP, the top institutions were the University of Pennsylvania (ACP value of 90.50), the University of Oxford (82.25), and the Mind Research Network (68.83).

There were 1506 authors that have contributed to research concerning information fusion for healthcare with AI. Table 7 presents the top 12 productive authors. Regarding productivity and influence measured by article count, the top three were Dinggang Shen, Daoqiang Zhang, and Vince D. Calhoun. Based on H-index, the top authors were Dinggang Shen, Vince D. Calhoun, and Hongzhi Wang. Regarding ACP, the top authors were Paul A. Yushkevich (ACP value of 156.20), Hongzhi Wang (131.50), and Jing Sui (84.40).

3.5. Top frequently used terms, phrases, and keywords

Table S2 in the **Appendix** lists the top-50 frequently used terms in titles and abstracts, in which “image” was the top one adopted in 184 articles (52.42%). Other frequently used terms included “multimodal (95 articles, 27.07%)”, “classifier (87, 24.79%)”, “deep (84, 23.93%)”, “segmentation (84, 23.93%)”, and “modality (82, 23.36%)”. The MK trend test results showed that most of the top-50 terms experienced a significant growth in usage, including “deep”, “segmentation”, “modality”, “convolutional”, “prediction”, “representation”, “cancer”, and “automatic”. **Table S3** in the **Appendix** presents the top-50 frequently used phrases in titles and abstracts, with “neural network” being the top one adopted in 65 articles (18.52%). Other frequently used phrases were “fusion method (35 articles, 9.97%)”, “deep learning (34, 9.69%)”, “magnetic resonance imaging (32, 9.12%)”, “label fusion (28, 7.98%)”, and “learning algorithm (26, 7.41%)”. Most of the phrases experienced a significant increase in usage, including “neural network”, “deep learning”, “medical image”, “computed tomography image”, “computed tomography”, “clinical application”, and “high-level feature”. Table 8 lists the top 50 frequently used keywords, with “human” being the top one adopted in 157 articles (44.73%). Other frequently used keywords were “algorithm (85 articles, 24.22%)”, “magnetic resonance imaging (77, 21.94%)”, “neural network (51, 14.53%)”, “article (50, 14.25%)”, “classification (50, 14.25%)”, “deep learning (47, 13.39%)”, and “computer-aided image processing (46, 13.11%)”. Most of the keywords experienced a significant growth in usage, including “deep learning”, “male”, “classification”, “computer-aided image processing”, “procedure”, “support vector machine”, “Alzheimer disease”, and “convolutional neural network”.

Fig. 5 visualizes the emerging phrases with an occurrence ranging from three to six during 2016–2020. Many important emerging issues were identified, including “skin cancer”, “genomic data”, “short-term memory”, “artificial intelligence”, “epileptic seizure detection”, “ensemble strategy”, “skin lesion”, “feature learning”, “multimodal classification”, and “multimodality fusion”. Fig. 6 visualizes the emerging keywords with an occurrence ranging from four to 13, including “transfer learning”, “deep neural network”, “brain diagnostic imaging”, “radiomics”, “structural magnetic resonance imaging”, “multimodal fusion”, and “feature fusion”. Indeed, the emerging keywords and phrases constitute potential directions for future research on information fusion for healthcare with AI.

Table 5
Top productive countries/regions.

C/R	A (R)	H (R)	C (R)	ACP
China	145 (1)	25 (2)	2463 (2)	16.99
USA	129 (2)	36 (1)	5064 (1)	39.26
UK	25 (3)	17 (3)	2400 (3)	96.00
India	23 (4)	9 (4)	464 (9)	20.17
South Korea	17 (5)	9 (4)	679 (7)	39.94
Canada	13 (6)	8 (6)	975 (4)	75.00
Australia	12 (7)	7 (7)	338 (10)	28.17
Germany	11 (8)	7 (7)	886 (5)	80.55
Iran	10 (9)	7 (7)	156 (15)	15.60
Saudi Arabia	8 (10)	7 (7)	83 (20)	10.38
Singapore	8 (10)	5 (12)	214 (12)	26.75
Spain	7 (12)	5 (12)	110 (18)	15.71

Abbreviations: C/R: country/region; R: ranking position; H: H-index; A: article count; C: citation count; ACP: average citations per article.

Table 6
Top productive institutions.

Institution	C/R	A (R)	H (R)	C (R)	ACP
University of North Carolina at Chapel Hill	USA	25 (1)	15 (1)	1041 (2)	41.64
Chinese Academy of Sciences	China	15 (2)	9 (2)	335 (13)	22.33
University of Pennsylvania	USA	10 (3)	9 (2)	905 (3)	90.50
Shanghai Jiao Tong University	China	9 (4)	7 (4)	550 (10)	61.11
Korea University	South Korea	8 (5)	6 (6)	623 (9)	77.88
Nanjing University of Aeronautics and Astronautics	China	8 (5)	5 (8)	135 (45)	16.88
University of Oxford	UK	8 (5)	7 (4)	658 (6)	82.25
National Institutes of Health	USA	7 (8)	4 (13)	80 (64)	11.43
Tsinghua University	China	7 (8)	5 (8)	71 (74)	10.14
COMSATS University Islamabad	Pakistan	6 (10)	6 (6)	75 (68)	12.50
The Mind Research Network	USA	6 (10)	4 (13)	413 (12)	68.83
Shandong University	China	6 (10)	3 (19)	228 (20)	38.00

Abbreviations: C/R: country/region; R: ranking position; H: H-index; A: article count; C: citation count; ACP: average citations per article.

Table 7
Top productive authors.

Authors	Current institution	A (R)	H (R)	C (R)	ACP
Dinggang Shen	ShanghaiTech University	24 (1)	14 (1)	966 (3)	40.25
Daoqiang Zhang	Nanjing University of Aeronautics and Astronautics	9 (2)	5 (4)	168 (58)	18.67
Vince D. Calhoun	University of New Mexico	8 (3)	6 (2)	446 (26)	55.75
Tao Zhou	Nanjing University of Science and Technology	7 (4)	5 (4)	125 (95)	17.86
Mingxia Liu	University of North Carolina at Chapel Hill	6 (5)	5 (4)	49 (235)	8.17
Kim-Han Thung	University of North Carolina at Chapel Hill	6 (5)	5 (4)	125 (95)	20.83
Hongzhi Wang	IBM Almaden Research Center	6 (5)	6 (2)	789 (4)	131.50
Anant Madabhushi	Emory University	5 (8)	5 (4)	253 (41)	50.60
Amjad Rehman	Prince Sultan University	5 (8)	5 (4)	68 (160)	13.60
Yinghuan Shi	Nanjing University	5 (8)	5 (4)	93 (143)	18.60
Jing Sui	Chinese Academy of Sciences	5 (8)	4 (12)	422 (27)	84.40
Paul A. Yushkevich	University of Pennsylvania	5 (8)	5 (4)	781 (5)	156.20

Abbreviations: R: ranking position; H: H-index; A: article count; C: citation count; ACP: average citations per article.

3.6. Topic identification and trend analysis

The 14 topics obtained from STM analysis are presented in Table 9, along with topic proportions and labels. The most-discussed topics were *magnetic resonance imaging and computed tomography data processing* (11.04%), *multimodality medical image fusion and fuzzy-based intelligent health and medical systems* (10.06%), *multi-atlas label fusion and segmentation* (9.41%), *smart devices, sensors, and infrastructure for intelligent health and medical systems* (8.99%), and *multimodal image fusion for brain disorders* (8.74%). We additionally identified representative studies for each topic, which are given in Table 10.

The MK test results indicated that four topics, including multimodality feature learning and representation for intelligent health and medical systems, magnetic resonance imaging and computed tomography data processing, prediction and computer-aided prognosis based on multimodal biomedical data, and multimodal image fusion for brain disorders exhibited a statistically significant increase in proportion. Fig. 7 depicts the annual trends of the 14 topics by displaying their varying prevalence in the data corpus.

3.7. Topic clustering

Fig. 8 presents the clustering analysis results, which provide insights into topics' interaction structures, similar to interdisciplinary analysis (Nichols, 2014). When two topics are often mentioned in the same document, then an interdisciplinary research area can be shaped. For instance, *smart devices, sensors, and infrastructure for intelligent health and medical systems* and *electrocardiogram analysis* show a high level of similarity. This suggests that documents having high relevance to *smart devices, sensors, and infrastructure for intelligent health and medical systems* are likely to be associated with *electrocardiogram analysis*. In other words, the close relationship between the two topics demonstrates that the technique of electrocardiogram analysis is popularly used to facilitate the establishment of *smart devices, sensors, and infrastructure for intelligent health and medical systems*.

3.8. Topic distributions of major contributors

Fig. 9 shows the topic distributions of productive publication sources, countries/regions, and institutions. Regarding publication sources (see Fig. 9(a)), IEEE Engineering in Medicine and Biology Society was the most productive in *electroencephalogram analysis*, and IEEE Transactions on Biomedical Engineering was the most productive in *magnetic resonance imaging and computed tomography data processing*. IEEE Journal of Biomedical and Health Informatics and Computer Methods and Programs in Biomedicine published more

Table 8
Top frequently used keywords.

Keyword	A	%	p	S	z	Trend	Keyword	A	%	p	S	z	Trend
human	157	44.73	0.5753	22	0.56032	↑	artificial intelligence	24	6.84	0.5542	-23	-0.59143	↓
algorithm	85	24.22	0.1848	50	1.3261	↑	middle aged	24	6.84	0.0099	89	2.5782	↑↑↑
magnetic resonance imaging	77	21.94	0.0252	83	2.2387	↑↑	brain	21	5.98	0.0073	90	2.6835	↑↑↑
neural network	51	14.53	0.0356	77	2.1017	↑↑	priority journal	21	5.98	0.0266	69	2.2175	↑↑
article	50	14.25	0.0054	90	2.7794	↑↑↑	three-dimensional imaging	21	5.98	0.0973	56	1.6583	↑
classification	50	14.25	0.0015	114	3.1725	↑↑↑	x-ray computed tomography	21	5.98	0.0013	104	3.2167	↑↑↑
deep learning	47	13.39	0.0005	96	3.5002	↑↑↑↑	computer aided signal processing	20	5.70	0.4287	28	0.79138	↑
Computer-aided image processing	46	13.11	0.0046	95	2.8355	↑↑↑	image enhancement	20	5.70	0.0838	60	1.7293	↑
female	45	12.82	0.0051	102	2.8012	↑↑↑	segmentation	20	5.70	0.0312	70	2.1548	↑↑
male	45	12.82	0.0007	122	3.3971	↑↑↑↑	electroencephalography	19	5.41	0.0860	61	1.7171	↑
procedure	44	12.54	0.0031	87	2.9597	↑↑↑	data fusion	18	5.13	0.0491	64	1.9675	↑↑
computer aided diagnosis	41	11.68	0.0275	78	2.2045	↑↑	multimodal imaging	18	5.13	0.0059	81	2.7532	↑↑↑
machine learning	41	11.68	0.0012	95	3.235	↑↑↑	artificial neural network	17	4.84	0.0070	68	2.698	↑↑↑
automated pattern recognition	37	10.54	0.1805	50	1.3392	↑	controlled study	17	4.84	0.0073	79	2.6843	↑↑↑
support vector machine	37	10.54	0.0010	110	3.2865	↑↑↑	image analysis	17	4.84	0.0027	93	3.0002	↑↑↑
computer aided image interpretation	36	10.26	0.5613	22	0.58095	↑	image fusion	17	4.84	0.0266	72	2.2173	↑↑
Alzheimer disease	34	9.69	0.0010	110	3.2865	↑↑↑	positron emission tomography	17	4.84	0.0019	104	3.1056	↑↑↑
sensitivity and specificity	34	9.69	0.0429	73	2.0244	↑↑	mild cognitive impairment	16	4.56	0.0036	80	2.9107	↑↑↑
adult	32	9.12	0.0117	87	2.5218	↑↑	fusion	15	4.27	0.0015	93	3.1661	↑↑↑
convolutional neural network	29	8.26	0.0011	82	3.2618	↑↑↑	neuroimaging	15	4.27	0.0048	83	2.822	↑↑↑
image segmentation	28	7.98	0.0013	108	3.2262	↑↑↑	subtraction technique	15	4.27	0.3612	29	0.9131	↑
reproducibility of result	28	7.98	0.1158	57	1.5728	↑	label fusion	14	3.99	0.0019	104	3.1056	↑↑↑
aged	27	7.69	0.0079	86	2.6545	↑↑↑	principal component analysis	14	3.99	0.0237	76	2.2613	↑↑
diagnostic imaging	27	7.69	0.0017	97	3.1306	↑↑↑	statistical model	14	3.99	0.0314	67	2.1523	↑↑
nuclear magnetic resonance imaging	27	7.69	0.0025	89	3.0285	↑↑↑	wavelet analysis	14	3.99	0.0030	96	2.9668	↑↑↑

Note: A: article count; %: proportion; increasing (decreasing) trend but not significant ($p > 0.05$); ↑↑(↓↓), ↑↑↑(↓↓↓), ↑↑↑↑(↓↓↓↓): significantly increasing (decreasing) trend ($p < 0.05$, $p < 0.01$, and $p < 0.001$, respectively); S: MK test statistics; z: z test statistics.

Fig. 5. Emerging key phrases during the period 2016–2020.

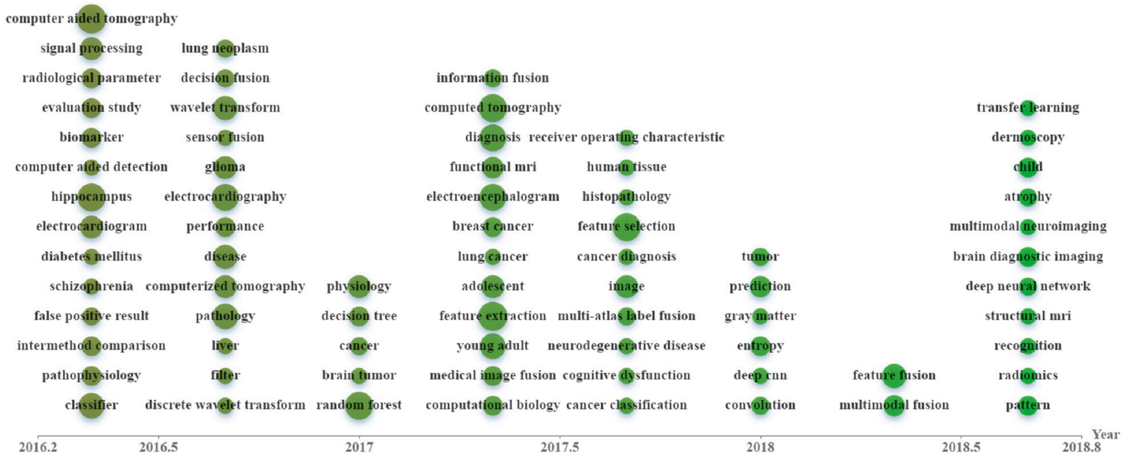


Fig. 6. Emerging keywords during the period 2016–2020.

studies concerning *electrocardiogram analysis*. Medical Image Analysis and Medical Image Computing and Computer-Assisted Intervention were the most productive in *multi-atlas label fusion and segmentation.* In addition, Journal of Medical Imaging and Health Informatics published many studies concerning *multimodality medical image fusion and fuzzy-based intelligent health and medical systems*.

In terms of countries/regions (see Fig. 9(b)), Iran and South Korea were the most productive in *multimodal image fusion for brain disorders*, and India was the most productive in *multimodality medical image fusion and fuzzy-based intelligent health and medical systems*. Canada and Australia published the most studies concerning *electroencephalogram analysis*, and the UK and Germany were the most productive in *statistical inference and models for multimodality data fusion*. In addition, China and the USA published many studies about *magnetic resonance imaging and computed tomography data processing* and *multi-atlas label fusion and segmentation*, respectively.

Concerning institutions (see Fig. 9(c)), the University of North Carolina at Chapel Hill, the University of Pennsylvania, Shanghai Jiaotong University, and Nanjing University of Aeronautics and Astronautics were the most productive in *multi-atlas label fusion and segmentation*. The University of Oxford and Tsinghua University were the most productive in *electrocardiogram analysis*. In addition, the Chinese Academy of Sciences and Korea University published many studies about *multimodal image fusion for brain disorders* and *multimodality feature learning and representation for intelligent health and medical systems*, respectively. We additionally identified top authors and institutions for each topic. The results are presented in Table 11 and Table S6 in the Appendix.

Table 9
The 14 topics with proportions, suggested labels, and trend test results.

Labels	%	p	S	z	Trend
multimodality feature learning and representation for intelligent health and medical systems	5.25	0.0024	81	3.0302	↑↑↑
magnetic resonance imaging and computed tomography data processing	11.04	0.0051	75	2.8029	↑↑↑
prediction and computer-aided prognosis based on multimodal biomedical data	7.67	0.0100	69	2.5757	↑↑
histopathological classification based on convolutional neural networks	7.30	0.0582	51	1.8939	↑
multimodality medical image fusion and fuzzy-based intelligent health and medical systems	10.06	0.8202	-7	-0.2273	↓
smart devices, sensors, and infrastructure for intelligent health and medical systems	8.99	1.0000	1	0.0000	↑
machine learning for biomedical and genomic data fusion	5.88	0.0690	49	1.8181	↑
human activity, disease, and mental state detection based on multimodality data	3.94	0.1297	41	1.5151	↑
multi-atlas label fusion and segmentation	9.41	0.1978	35	1.2878	↑
multimodal image fusion for brain disorders	8.74	0.0040	77	2.8787	↑↑↑
statistical inference and models for multimodality data fusion	3.25	1.0000	1	0.0000	↑
electroencephalogram analysis	7.47	0.7619	-9	-0.3030	↓
electrocardiogram analysis	7.03	0.1501	39	1.4394	↑
electroencephalogram and functional magnetic resonance imaging integration	3.97	0.8202	7	0.2273	↑

Note: FREX and abbreviations are shown in **Tables S4** and **S5** in the **Appendix**. %: proportion; increasing (decreasing) trend but not significant ($p > 0.05$); ↑↑(↓↓), ↑↑↑(↓↓↓), ↑↑↑↑(↓↓↓↓): significantly increasing (decreasing) trend ($p < 0.05$, $p < 0.01$, and $p < 0.001$, respectively); S: MK test statistics; z: z test statistics.

3.9. Trends of issues and techniques in each topic

The evolution of major issues and techniques in each topic was explored. Specifically, for the top representative articles (with a probability of more than 90%) of each topic, the keywords and phrases used in titles and abstracts were identified and analyzed using VOSviewer[5] (see Fig. 10), with node color representing the average publication year and node size indicating the occurrence in the data corpus. Several important implications were detected.

For the majority of the 14 topics, as time passed, increasingly diverse techniques were adopted. Most importantly, there was increased use of advanced deep learning algorithms in various aspects of medical/health information fusion research, especially for certain topics, such as *multimodality feature learning and representation for intelligent health and medical systems, prediction and computer-aided prognosis based on multimodal biomedical data, electrocardiogram analysis*, as well as *human activity, disease, and mental state detection based on multimodality data*. Moreover, basic AI algorithms and statistical methodologies (e.g., SVMs, machine learning, neural networks, principal component analysis (PCA), ensemble learning, clustering, classification, and hidden Markow models) appeared relatively early. On the other hand, advanced deep learning algorithms (e.g., DNNs, CNNs, artificial neural networks, and fuzzy logic) have become popular in recent years.

Secondly, the diversity of issues and techniques involved in each of the 14 topics was inconsistent. Some topics seemed to express interest in diverse issues and techniques, for example, *multimodality medical image fusion and fuzzy-based intelligent health and medical systems, smart devices, sensors, and infrastructure for intelligent health and medical systems, multi-atlas label fusion and segmentation*, and *multimodal image fusion for mental diseases*. However, in some other topics, there was less concern about diverse issues and techniques, for example, *machine learning for biomedical and genomic data fusion, human activity, disease, and mental state detection based on multi-modality data*, and *statistical inference models for multimodality data fusion*.

The results indicate the significant issues and their evolutions in each topic. Due to space limitations, we provide an interpretation example for the topic of *multimodal image fusion for mental diseases*. In 2015–2016, schizophrenia among female and male adults was widely studied using multimodal imaging, SVMs, correlation analysis, multimodal data fusion, and MRI data fusion. Around 2017–2018, neurodegenerative diseases, especially Alzheimer's disease, based on machine learning and feature fusion strategies and PET, functional connectivity network, and fMRI data have received increased attention. Moreover, an emerging research trend on memory was noteworthy during this period. From 2019 to 2020, there was an emphasis on the study of mental or brain diseases and cognitive symptoms, particularly depression and mild cognitive impairment (MCI), with the adoption of diverse techniques or strategies, such as multiclass SVM and multi-feature fusion. In addition to adults, children received intense attention during this period, with complementary information being increasingly used for data analysis and segmentation.

3.10. Scientific collaboration analysis

Fig. 11(a) depicts the collaborations among countries/regions with a collaborative frequency ranging from five to 40. The USA and China were the closest partners, collaborating in 40 articles, followed by the USA and South Korea (11), Pakistan and Saudi Arabia (six), and Australia and China (six). Fig. 11(b) shows the collaborations among countries/regions with a collaborative frequency of four. A collaborative cluster formed by South Korea, Singapore, and China is noteworthy, all of which are from the Asian region.

Fig. 12(a) depicts collaborations among institutions with a collaborative frequency ranging from four to eight, comprising six institutions. Korea University and the University of North Carolina at Chapel Hill were the closest collaborators in eight articles,

[5] https://www.vosviewer.com/

Table 10
Representative studies for each topic

Topic	Studies	Title	C
multimodality feature learning and representation for intelligent health and medical systems	Zhou, Liu, Thung, & Shen, 2019	"latent representation learning for Alzheimer's disease diagnosis with incomplete multi-modality neuroimaging and genetic data"	23
	Zhou, Thung, Zhu, & Shen, 2017	"feature learning and fusion of multimodality neuroimaging and genetic fata for multi-status dementia diagnosis"	17
	Zhou, Liu, Thung, & Shen, 2019	"effective feature learning and fusion of multimodality data using stage-wise deep neural network for dementia diagnosis"	51
magnetic resonance imaging and computed tomography data processing	van Sloun et al. (2021)	"deep learning for real-time, automatic, and scanner-adapted prostate (zone) segmentation of transrectal ultrasound, for example, magnetic resonance imaging–transrectal ultrasound fusion prostate biopsy"	11
	Zhuge et al. (2017)	"brain tumor segmentation using holistically nested neural networks in MRI images"	34
	Tang et al. (2020)	"postoperative glioma segmentation in CT image using deep feature fusion model guided by multi-sequence MRIs"	1
prediction and computer-aided prognosis based on multimodal biomedical data	Golugula et al. (2011)	"supervised regularized canonical correlation analysis: integrating histologic and proteomic measurements for predicting biochemical recurrence following prostate surgery"	40
	Madabhushi et al. (2011)	"computer-aided prognosis: predicting patient and disease outcome via quantitative fusion of multi-scale, multi-modal data"	113
	Dong et al. (2019)	"MLW-gcForest: a multi-weighted gcForest model towards the staging of lung adenocarcinoma based on multi-modal genetic data"	0
histopathological classification based on convolutional neural networks	Mahbod et al. (2020)	"transfer learning using a multi-scale and multi-network ensemble for skin lesion classification"	4
	Yang et al. (2019)	"noninvasive evaluation of the pathologic grade of hepatocellular carcinoma using MCF-3DCNN: a pilot study"	2
	Banerjee et al. (2018)	"transfer learning on fused multiparametric MR images for classifying histopathological subtypes of rhabdomyosarcoma"	29
multimodality medical image fusion and fuzzy-based intelligent health and medical systems	Li et al. (2017)	"edge-preserve filter image enhancement with application to medical image fusion"	8
	Soundrapandiyan et al. (2016)	"multimodality medical image fusion using block based intuitionistic fuzzy sets"	0
	Yang et al. (2018)	"multimodal medical image fusion based on fuzzy discrimination with structural patch decomposition"	7
smart devices, sensors, and infrastructure for intelligent health and medical systems	Hsu et al. (2017)	"design and implementation of a smart home system using multisensor data fusion technology"	47
	Wu et al. (2018)	"sensor fusion for recognition of activities of daily living"	19
	Sun et al. (2020)	"state recognition of decompressive laminectomy with multiple information in robot-assisted surgery"	1
machine learning for biomedical and genomic data fusion	Yu et al. (2010)	"L2-norm multiple kernel learning and its application to biomedical data fusion"	113
	An et al. (2019)	"an efficient feature extraction technique based on local coding PSSM and multifeatures fusion for predicting protein-protein interactions"	2
	Arvind et al. (2018)	"predicting surgical complications in adult patients undergoing anterior cervical discectomy and fusion using machine learning"	16
human activity, disease, and mental state detection based on multimodality data	Tran et al. (2017)	"continuous detection of human fall using multimodal features from Kinect sensors in scalable environment"	23
	Ni et al. (2013)	"multilevel depth and image fusion for human activity detection"	99
	Samareh et al. (2018)	"detect depression from communication: how computer vision, signal processing, and sentiment analysis join forces"	3
multi-atlas label fusion and segmentation	Sanroma et al. (2015)	"a transversal approach for patch-based label fusion via matrix completion"	25
	Plassard & Landman (2017)	"multiprotocol, multiatlas statistical fusion: theory and application"	0
	Huo et al. (2017)	"4D multi-atlas label fusion using longitudinal images"	3
multimodal image fusion for brain disorders	Plis et al. (2018)	"reading the (functional) writing on the (structural) wall: multimodal fusion of brain structure and function via a deep neural network based translation approach reveals novel impairments in schizophrenia"	16
	Maglanoc et al. (2020)	"multimodal fusion of structural and functional brain imaging in depression using linked independent component analysis"	6
	Jie et al. (2015)	"discriminating bipolar disorder from major depression based on SVM-FoBa: efficient feature selection with multimodal brain imaging data"	57
statistical inference and models for multimodality data fusion	Aluja-Banet et al. (2015)	"improving prevalence estimation through data fusion: methods and validation"	2
	Rohe & Noppeney (2015)	"cortical hierarchies perform Bayesian causal inference in multisensory perception"	159
	Rohe et al. (2019)	"the neural dynamics of hierarchical Bayesian causal inference in multisensory perception"	27

(continued on next page)

Table 10 (*continued*)

Topic	Studies	Title	C
electroencephalogram analysis	Li et al. (2017)	"a motion-classification strategy based on sEMG-EEG signal combination for upper-limb amputees"	66
	Li et al. (2020)	"multi-feature fusion method based on EEG signal and its application in stroke classification"	1
	Sun et al. (2019)	"epileptic seizure detection with EEG textural features and imbalanced classification based on EasyEnsemble learning"	9
Electrocardiogram analysis	Chen et al. (2020a)	"multi-information fusion neural networks for arrhythmia automatic detection"	2
	Liu, Zhou, Hu, & Wu, 2018	"signal quality index-based two-step method for heart rate estimation by combining electrocardiogram and arterial blood pressure signals"	2
	Pimentel et al. (2015)	"heart beat detection in multimodal physiological data using a hidden semi-Markov model and signal quality indices"	39
electroencephalogram and functional magnetic resonance imaging integration	Daunizeau et al. (2007)	"symmetrical event-related EEG/fMRI information fusion in a variational Bayesian framework"	152
	Ertugrul et al. (2018)	"hierarchical multi-resolution mesh networks for brain decoding"	2
	Ahmad et al. (2017)	"visual brain activity patterns classification with simultaneous EEG-fMRI: a multimodal approach"	1

Note: C: citation count.

followed by Prince Sultan University and COMSATS University (five), HITEC University and COMSATS University (four), and Nanjing University and the University of North Carolina at Chapel Hill (four). Fig. 12(b) presents collaborations among institutions with a collaborative frequency of three. Three clusters are identified, including (1) HITEC University and Prince Sultan University; (2) Korea University and the University of North Carolina at Chapel Hill; and (3) the Chinese Academy of Sciences, the University of New Mexico, the Mind Research Network, Al Yamamah University, COMSATS University, and the University of the Chinese Academy of Sciences.

Fig. 13(a) depicts collaborations among authors with a collaborative frequency ranging from five to six, comprising a total of eight authors. Dinggang Shen and Kim-Han Thung were the closest collaborators in six articles, followed by Jing Sui and Vince D. Calhoun (five), Paul A. Yushkevich and Hongzhi Wang (five), Tao Zhou and Dinggang Shen (five), Kim-Han Thung and Tao Zhou (five), and Yinghuan Shi and Dinggang Shen (five). Fig. 13(b) presents collaborations among authors with a collaborative frequency of four. Four clusters are identified, including (1) Yuhui Du, Vince D. Calhoun, Tianzi Jiang, and Jing Sui; (2) Anant Madabhushi and George Lee; (3) Muhammad Attique Khan and Amjad Rehman; and (4) Yang Gao, Yinghuan Shi, Daoqiang Zhang, Guorong Wu, Yaozong Gao, Feng Shi, and Mingxia Liu.

3.11. Scientific collaborative patterns in each topic

The collaborative patterns in each of the 14 topics were explored to determine "which topics were more collaborative" and "what countries/regions and institutions were collaborative in conducting particular research". To be specific, we visualized the collaborative patterns in the top representative articles (with a probability of more than 90%) of each topic (see Fig. 14). We only considered the collaborative partners with a collaborative frequency of more than one for a better interpretation. From the perspective of countries/regions (see Fig. 14(a)), China and the USA were the top collaborative countries on almost all topics. Several topics attracted more international collaborations, for example, *magnetic resonance imaging and computed tomography data processing, histopathological classification based on convolutional neural networks*, and *electroencephalogram and functional magnetic resonance imaging integration*. Comparatively, several topics appeared to be less attractive for international collaborators, including *prediction and computer-aided prognosis based on multimodal biomedical data* and *multimodality medical image fusion and fuzzy-based intelligent health and medical systems*. From an institutional perspective (see Fig. 14(b)), the University of North Carolina at Chapel Hill was especially active in international collaborations. Several topics attracted more cross-institutional collaborations, for example, *histopathological classification based on convolutional neural networks* and *multimodal image fusion for mental diseases*. Comparatively, several topics seemed less attractive for cross-institutional collaborators, including *magnetic resonance imaging and computed tomography data processing* and *prediction and computer-aided prognosis based on multimodal biomedical data*. From an author's perspective (see Fig. 14(c)), Dinggang Shen was especially active in international collaborations. Several topics attracted more collaborations, for example, *multimodality feature learning and representation for intelligent health and medical systems* and *magnetic resonance imaging and computed tomography data processing*. Comparatively, several topics seemed less attractive for collaborators, including *machine learning for biomedical and genomic data fusion, statistical inference and models for multimodality data fusion*, and *electroencephalogram analysis*.

4. Discussion

This study offers a systematic overview and state-of-the-art understanding of scientific studies focusing on information fusion for healthcare with AI. By using topic modeling and bibliometric analysis methodologies, we present essential results related to the trends, journals, countries/regions, institutions, and authors along with their scientific collaborations, predominant research topics and their changes in prevalence, as well as topic distributions across journals, countries/regions, institutions, and authors. In response to the research questions, the following sections discuss the findings derived from the data analysis.

4.1. Publication trends, publication sources, contributors, scientific collaboration, and topic distributions across contributors

In response to RQ1, the continuing increase in the annual academic output indicates an ongoing rise of interest in this important interdisciplinary field. Research on information fusion for healthcare with AI thus constitutes a prospective scientific field with rapid growth and expansion of community and academic achievements. The publication source analysis (Table 4) stresses the popularity of studies helping to increase knowledge about the ways that AI facilitates medical information fusion to support decision-making in interdisciplinary publication sources with a dual focus on both medical or healthcare and computer science. The statistical analysis of countries/regions, institutions, and authors (Tables 5, 6 and 7) indicates that researchers in various countries/regions (e.g., the USA, China, the UK) and institutions (University of North Carolina at Chapel Hill and Chinese Academy of Sciences) were increasingly interested in the field, with China contributing to more than 40% of the studied corpus.

In response to RQ5, the network visualization (Figs. 11, 12 and 13) shows that the countries/regions, institutions, and authors with an enthusiastic attitude towards international collaborations showed higher productivity and broader impact. Examples involve the USA, China, the UK, and Canada from a regional perspective, the University of North Carolina at Chapel Hill, and the Chinese Academy of Sciences from an institutional perspective, as well as Dinggang Shen, Vince D. Calhoun, and Tao Zhou from an author perspective. These results reflect that international collaborations are significant in facilitating the development of such an increasingly active, promising, and novel interdisciplinary research field, mainly through the mutual embrace of its benefits and potential challenges. The findings highlight the significance of intra-regional and intra-institutional collaborations, which are expected to expand markedly in the future.

In response to RQ4, the quantitative analysis and visualization of the topical distributions (Fig. 9 and Table 11**)** reveal the research strength of countries/regions, institutions, and authors in one or more topics. From a regional perspective, countries/regions had comparatively distributed interests in every aspect of research on information fusion for healthcare with AI. However, institutions and authors tended to focus on specific topics. The diversity of topical distributions indicates that more effective research on information fusion for healthcare with AI depends upon inter-regional, inter-institutional, and interdisciplinary scientific cooperation. The network visualization of the collaborations among countries/regions, institutions, and authors from a topic-wise perspective (Fig. 10) further reflects that countries/regions, institutions, or authors having similar research interests are more likely to cooperate to integrate academic strengths to address challenges/difficulties and to promote the field's development. Therefore, institutions and researchers are advised to collaborate with potential partners, particularly those with similar research strengths and interests, to jointly investigate the possibilities of adopting AI technologies for medical information fusion to facilitate optimal decision-making in dealing with various medical or healthcare challenges.

4.2. Research topics and their changes in prevalence

The results of topic modeling (Table 9) and the topical trend analysis and visualization (Fig. 7) respond to RQ2 and RQ3, illustrating topical groups regarding the degree of prevalence. Firstly, two frequently discussed topics, including *multimodality medical image fusion and fuzzy-based intelligent health and medical systems* and *magnetic resonance imaging and computed tomography data processing*, have a proportion of over 10% each. The popularity of these two topics has also been verified by the results of the frequently used term/phrase/keyword analysis (Tables 8**,** S2, and S3; Figs. 5 and 6), with "image", "multimodal", "fusion method", "magnetic resonance imaging", "medical image fusion", "fused image", "magnetic resonance imaging", and "computed tomography image" being discussed frequently. Among the two topics, *magnetic resonance imaging and computed tomography data processing* showed a significantly growing tendency. Such a result suggests that research on this topic is likely to be a continuing focus. Comparatively, the other topic, i.e., *multimodality medical image fusion and fuzzy-based intelligent health and medical systems*, has no significant tendency. Such a result reflects that although this topic received much interest during the studied period (10.06%), it had a slow increase in research interest; thus, its developmental momentum would be less likely to retain.

Secondly, seven topics with a proportion between 7% and 10% together account for 56.61% of the data corpus (Table 9). These topics concentrate on fusion approaches (e.g., label fusion and segmentation) driven by deep neural networks based on electroencephalogram and electrocardiogram data for disease diagnosis and medical system design. The prevalence of these topics is also supported by the frequently used terms, phrases, and keywords (Tables 8**,** S2, and S3), for example, "segmentation", "system", "convolutional", "label", "neural network", "deep learning", "label fusion", and "classification". Only two of them, *multimodal image fusion for brain disorders* and *computer-aided prognosis based on multimodal biomedical data*, have enjoyed significantly growing tendencies. The two topics are very likely to be continuing hotspots. Comparatively, research interests in the other six topics, including *multi-atlas label fusion and segmentation, smart devices, sensors, and infrastructure for intelligent health and medical systems, electroencephalogram analysis, histopathological classification based on convolutional neural networks*, and *electrocardiogram analysis*, showed decreasing tendencies; thus, they are unlikely to retain developmental momentum.

Thirdly, the remaining five topics have a low proportion of below 6%. These topics focus on multimodality data integration and fusion based on statistical inference and modeling, feature learning and representation, and machine learning modeling. The prevalence of these topics is also supported by the results of term, phrase, and keyword analyses (Tables 8**,** S2, and S3), for example, "representation", "machine learning", "support vector machine", and "feature extraction". Among the five topics, only *multimodality feature learning and representation for intelligent health and medical systems* have shown a significantly growing tendency, indicating its great potential in increasing interest and attention. Four topics, including *machine learning for biomedical and genomic data fusion, electroencephalogram and functional magnetic resonance imaging integration, human activity, disease, and mental state detection based on multimodality data*, and *statistical inference and models for multimodality data fusion*, showed no significant tendency. Such a result

Fig. 7. Annual trends of the 14 topics.

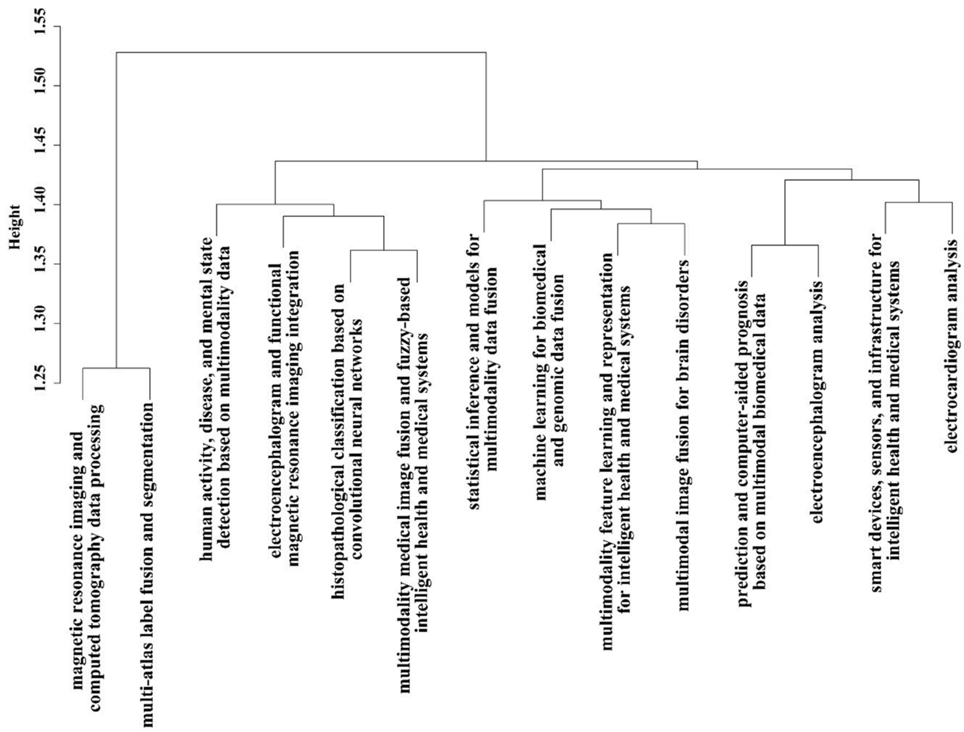


Fig. 8. Clustering analysis between the 14 identified topics.

indicates that these topics are less likely to be prevalent in the field of information fusion for healthcare with AI research.

4.3. Insights into essential issues and future directions of the field

The results of topic modeling, term/phrase/keyword analysis, development trend analysis, and visualization bring insights into essential issues and the possible future directions of the field of information fusion for healthcare with AI. We established ten themes by primarily focusing on the 12 topics showing increasing tendencies, especially the four with significant effects (Table 9 and Fig. 7), as well as the top frequently used keywords and the emerging keywords (Table 8, Fig. 5, and Fig. 6).

Specifically, the first theme, "application of AI-related technologies", was formed to cover the common concern of AI-related topics (e.g., *histopathological classification based on convolutional neural networks* and *machine learning for biomedical and genomic data fusion*), whose representative articles concentrated mainly on AI technologies. The AI-related terms, phrases, and keywords (e.g., "deep neural network", "short-term memory", "neural network", "deep learning", "machine learning", and "support vector machine") that are frequently studied among scholars also support the determination of the first theme. The second theme focusing on "brain disorder diagnosis based on multimodality data fusion" was formed by considering the increasingly prevalent topic of *multimodal image fusion for brain disorders* and an increase in interest in "brain diagnostic imaging". Third, we formed a theme of "multimodal neuroimaging fusion" because the representative studies of several topics (e.g., *magnetic resonance imaging and computed tomography data processing, electrocardiogram analysis, electroencephalogram, and functional magnetic resonance imaging integration*, and *statistical inference and models for multimodality data fusion*) center on multimodal neuroimaging data fusion (e.g., "structural magnetic resonance imaging"). The fourth theme, "multi-sensor data fusion for smart health", was constructed to discuss 8.99% of the studies that focus on "smart devices, sensors, and infrastructure for intelligent health and medical systems". We formed the fifth theme, "multimodal biomedical data fusion", by considering the most representative studies of two topics (i.e., *prediction and computer-aided prognosis based on multimodal biomedical data* and *machine learning for biomedical and genomic data fusion*) that involve multimodal biomedical data fusion.

Subsequently, a sixth theme, "multi-atlas label fusion", was established to cover the common concern of the topic *of multi-atlas label fusion and segmentation*. Scholars' frequent usage of keywords "multi-atlas segmentation" and "multi-atlas label fusion" also supports such a determination. The seventh theme, "emotion detection and recognition", was constructed to discuss the increase in interest in the topic of *human activity, disease, and mental state detection based on multimodality data* and the emergence of the keyword "epileptic seizure detection". Eighth, the theme "deep learning-based multi-view fusion" was formed by considering that multi-view fusion has been a popular strategy in studies related to feature learning and representation, especially concerning the topic *of multimodality feature learning and representation for intelligent health and medical systems*; plus, "feature learning" and "feature fusion" have also been identified as emerging topics in the field of information fusion for healthcare with AI. We further formed a theme of "automated skin lesion diagnosis" because of the emerging interest in "skin lesion" and "skin cancer", as well as a popular concern of skin lesion

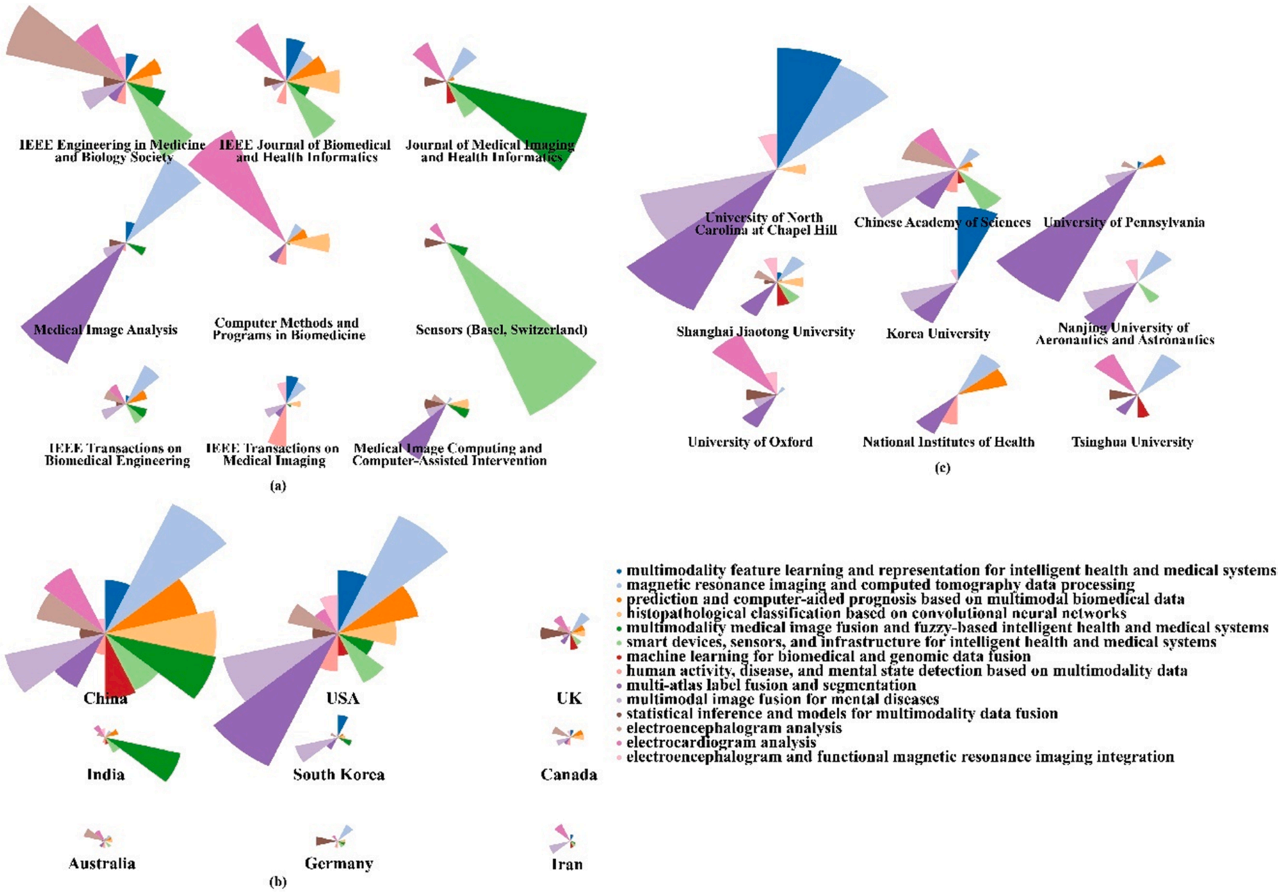
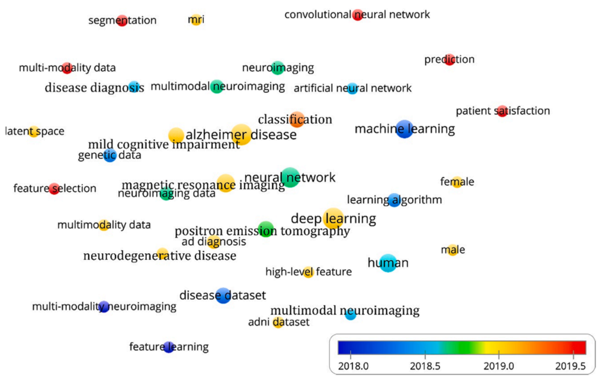


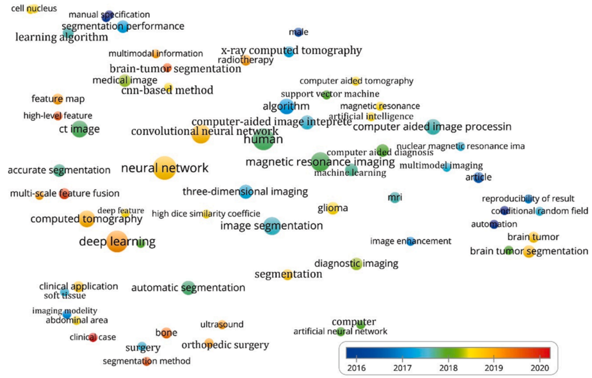
Fig. 9. Topic distributions of productive publication sources (a), countries/regions (b), and institutions (c).

Table 11
Top authors for each topic

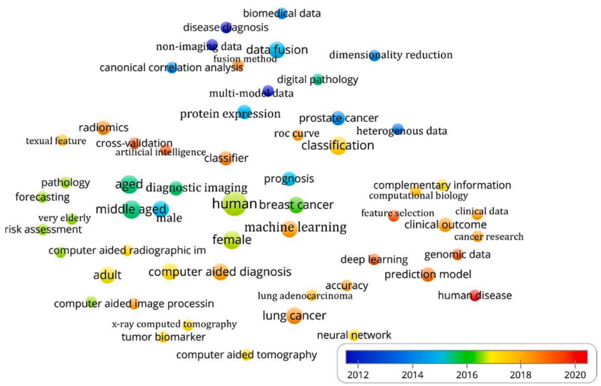
multimodality feature learning and representation for intelligent health and medical systems			magnetic resonance imaging and computed tomography data processing			prediction and computer-aided prognosis based on multimodal biomedical data		
Author	Institution	%	Author	Institution	%	Author	Institution	%
Dinggang Shen	University of North Carolina at Chapel Hill	5.30	Dinggang Shen	University of North Carolina at Chapel Hill	4.23	Anant Madabhushi	Case Western Reserve University	4.33
Tao Zhou	University of North Carolina at Chapel Hill	5.13	Yaozong Gao	United Imaging Intelligence	2.63	George Lee	Bristol-Myers Squibb	3.96
Kim-Han Thung	University of North Carolina at Chapel Hill	4.82	Yinghuan Shi	Nanjing University	2.63	Bin Zheng	University of Oklahoma	3.31
Mingxia Liu	University of North Carolina at Chapel Hill	2.86	Shu Liao	United Imaging Intelligence	2.63	Satish Viswanath	Case Western Reserve University	2.34
Xiaofeng Zhu	Massey University	1.97	Daoqiang Zhang	Nanjing University of Aeronautics and Astronautics	2.46	Pallavi Tiwari	Case Western Reserve University	2.34
histopathological classification based on convolutional neural networks			multimodality medical image fusion and fuzzy-based intelligent health and medical systems			smart devices, sensors, and infrastructure for intelligent health and medical systems		
Author	Institution	%	Author	Institution	%	Author	Institution	%
Rupert Ecker	Research and Development Department of TissueGnostics GmbH	1.97	P. Ganasala	Gayatri Vidya Parishad College of Engineering	1.97	Jie Hu	Wuhan University of Technology	1.97
Amirreza Mahbod	Medical University of Vienna	1.97	V. Kumar	JAYPEE University of Information Technology	1.97	Li Wang	Chinese Academy of Sciences	0.99
Gerald Schaefer	Loughborough University	1.97	Shuying Huang	Jiangxi University of Finance and Economics	1.96	Chih-Chien Chang	Feng Chia University	0.99
Chunliang Wang	KTH Royal Institute of Technology	1.97	Yong Yang	Jiangxi University of Finance and Economics	1.96	Hsing-Cheng Chang	Feng Chia University	0.99
Xi Wu	Chengdu University of Information Technology	1.96	Sudeb Das	Videonetics Pvt. Ltd	1.96	Yuan-Sheng Cheng	Feng Chia University	0.99
machine learning for biomedical and genomic data fusion			human activity, disease, and mental state detection based on multimodality data			multi-atlas label fusion and segmentation		
Author	Institution	%	Author	Institution	%	Author	Institution	%
Yves Moreau	University of Leuven	1.98	Amjad Rehman	Prince Sultan University	1.28	Dinggang Shen	University of North Carolina at Chapel Hill	6.68
Leon-Charles Tranchevent	University of Luxembourg	1.98	Muhammad Attique Khan	HITEC University	1.28	Hongzhi Wang	IBM Almaden Research Center	4.91
Amjad Rehman	Prince Sultan University	1.32	Lauren Kim	Brigham and Women's Hospital	1.12	Paul A. Yushkevich	University of Pennsylvania	4.53
Muhammad Attique Khan	HITEC University	1.32	Jiamin Liu	National Institutes of Health	1.12	Bennett A. Landman	Vanderbilt University	3.94
Jie Tian	Chinese Academy of Sciences	1.30	Le Lu	Johns Hopkins University	1.12	Guorong Wu	University of North Carolina at Chapel Hill,	3.91
multimodal image fusion for brain disorders			statistical inference and models for multimodality data fusion			electroencephalogram analysis		
Author	Institution	%	Author	Institution	%	Author	Institution	%
Vince D. Calhoun	Georgia State University	5.35	Uta Noppeney	University of Birmingham	1.97	Weidong Zhou	Shandong University	2.95
Dinggang Shen	University of North Carolina at Chapel Hill	4.98	Tim Rohe	Friedrich-Alexander University Erlangen-Nuernberg	1.97	Qi Yuan	Shandong Normal University	1.97
Jing Sui	Chinese Academy of Sciences	3.37	Tomas Aluja-Banet	Universitat Politècnica de Catalunya	0.99	Peng Fang	Chinese Academy of Sciences (CAS)	0.99
Tianzi Jiang	Chinese Academy of Sciences	3.37	Nuria Brunso	Institut d'Estadística de Catalunya	0.99	Guanglin Li	Chinese Academy of Sciences (CAS)	0.99
Juan Bustillo	University of New Mexico	2.41	Josep Daunis-i-Estadella	Universitat de Girona	0.99	Xiangxin Li	Chinese Academy of Sciences (CAS)	0.99
electrocardiogram analysis			electroencephalogram and functional magnetic resonance imaging integration					
Author	Institution	%	Author	Institution	%			
Jianqing Li	Nanjing Medical University	1.98	Vince D. Calhoun	Georgia State University	1.97			
Chengyu Liu	Southeast University	1.98	Dinggang Shen	University of North Carolina at Chapel Hill	1.54			
Shoushui Wei	Shandong University	1.98	Sui, Jing	Chinese Academy of Sciences	0.99			
Ye Li	Chinese Academy of Sciences	1.98	Yuhui Du	Shanxi University	0.99			
Chuang Han	Zhengzhou University	1.97	Habib Benali	Concordia University	0.99			



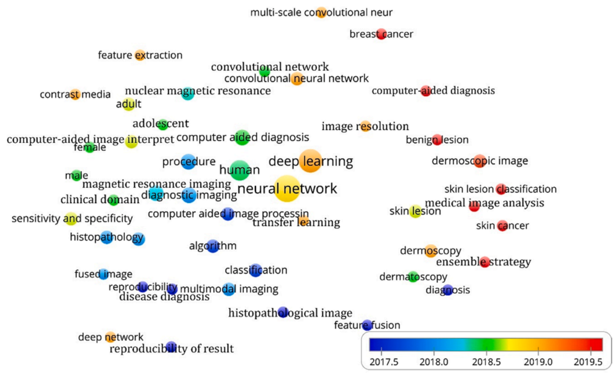
(a) Topic: multimodality feature learning and representation for intelligent health and medical systems



(b) Topic: magnetic resonance imaging and computed tomography data processing

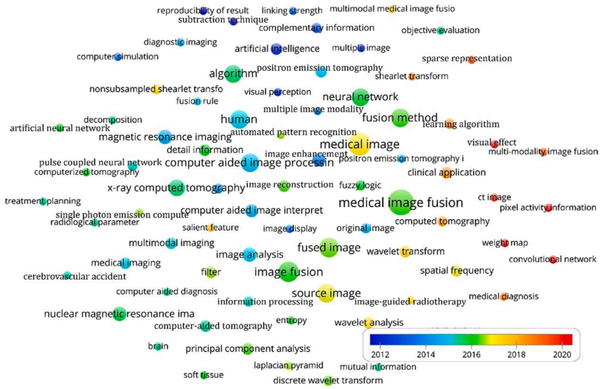


(c) Topic: prediction and computer-aided prognosis based on multimodal biomedical data

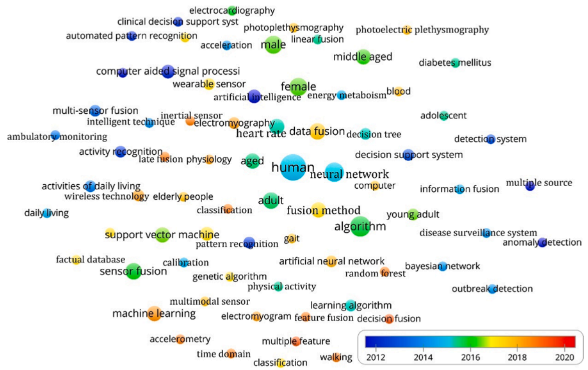


(d) Topic: histopathological classification based on convolutional neural networks

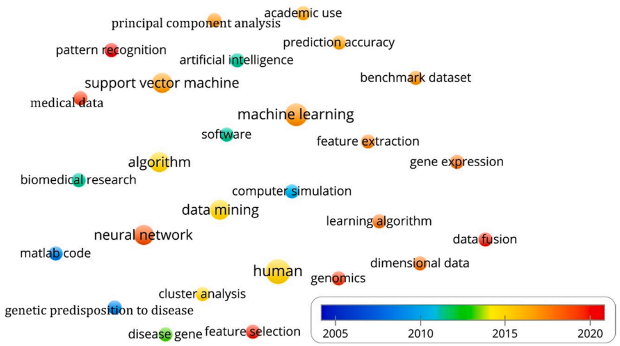
Fig. 10. Trends of issues and techniques in each topic.



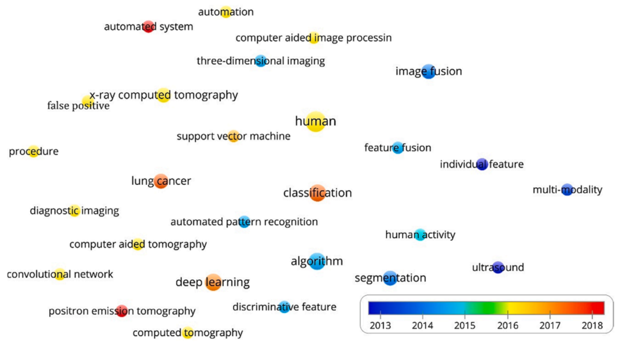
(e) Topic: multimodality medical image fusion and fuzzy-based intelligent health and medical systems



(f) Topic: smart devices, sensors, and infrastructure for intelligent health and medical systems

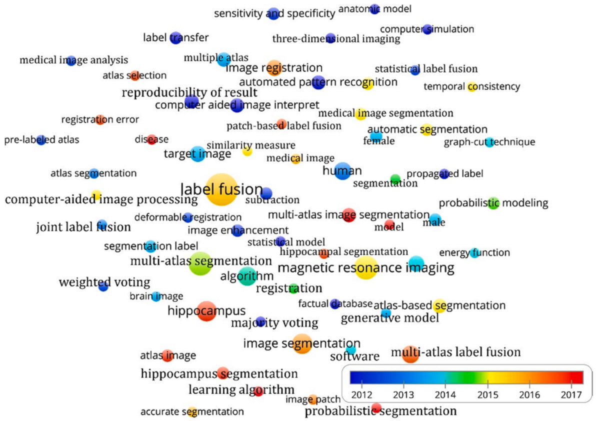


(g) Topic: machine learning for biomedical and genomic data fusion

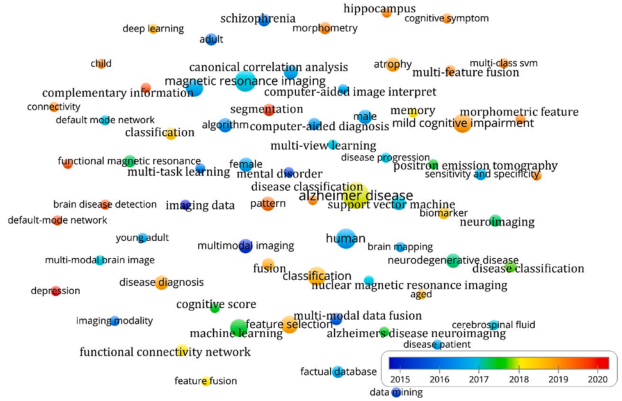


(h) Topic: human activity, disease, and mental state detection based on multimodality data

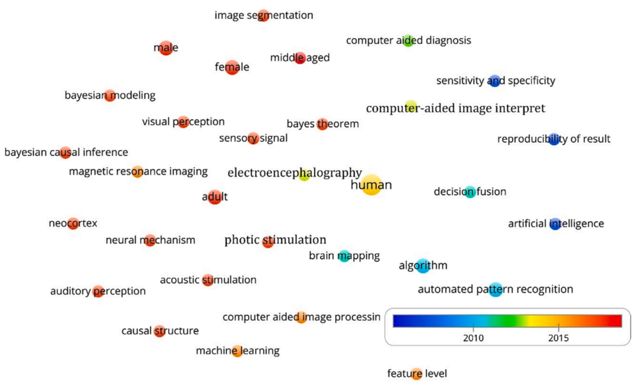
Fig. 10. (*continued*).



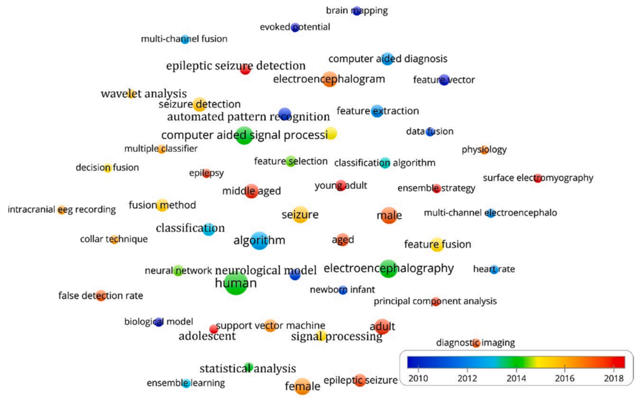
(i) Topic: multi-atlas label fusion and segmentation



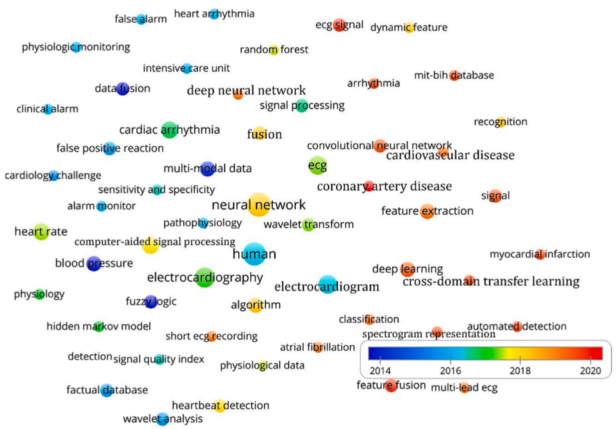
(j) Topic: multimodal image fusion for mental diseases



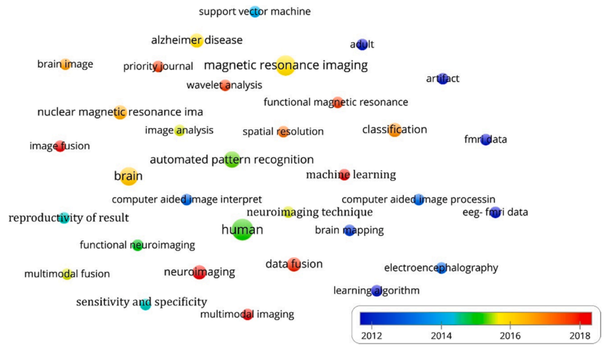
(k) Topic: statistical inference and models for multimodality data fusion



(l) Topic: electroencephalogram analysis



(m) Topic: electrocardiogram analysis



(n) Topic: electroencephalogram and functional magnetic resonance imaging integration

Fig. 10. (*continued*).

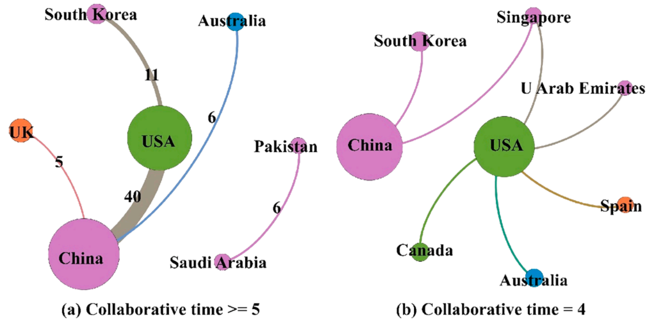


Fig. 11. Collaborations among countries/regions with a collaborative frequency ranging from four to 40.

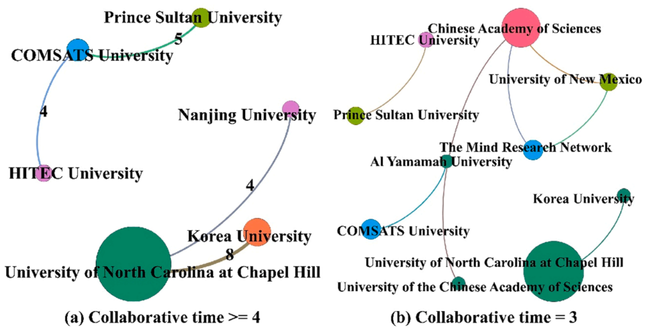


Fig. 12. Collaborations among institutions with a collaborative frequency ranging from three to eight.

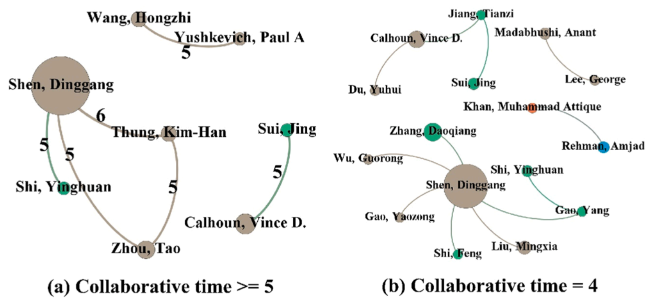


Fig. 13. Collaborations among authors with a collaborative frequency ranging from four to six.

diagnosis in representative studies of the topic *of histopathological classification based on convolutional neural networks*. We also formed the tenth theme, “fusion strategies based on transfer learning”, to discuss an emerging research interest in “transfer learning”, which is also a common strategy adopted by researchers focusing on the topic *of histopathological classification based on convolutional neural networks*. The following discussion is developed by tightly aligning to the ten themes.

4.3.1. Application of AI-related technologies

AI technologies are increasingly important in research concerning information fusion for healthcare. A range of AI technologies and applications such as feature learning and representation, CNNs, fuzzy-based algorithms, machine learning, and intelligent health and medical systems have been identified. The popularity of AI-related technologies and applications is possibly a consequence of recent advancements in machine learning and AI approaches aiming at building “intelligent agents” that are able to “correctly interpret external data, learn from these data, and use the learned knowledge for cognitive tasks like reasoning, planning, problem-solving, decision making, motion and manipulation” (Leung et al., 2019). Within the field of AI, machine learning, and particularly deep learning, have recently received increased attention from scholars. AI-related technologies are widely utilized in different areas, including facilitating tasks, for example, disease diagnosis, automatic brain image segmentation, disease outcome prediction, skin lesion classification, and human activity detection through medical information fusion. Among the numerous technologies and

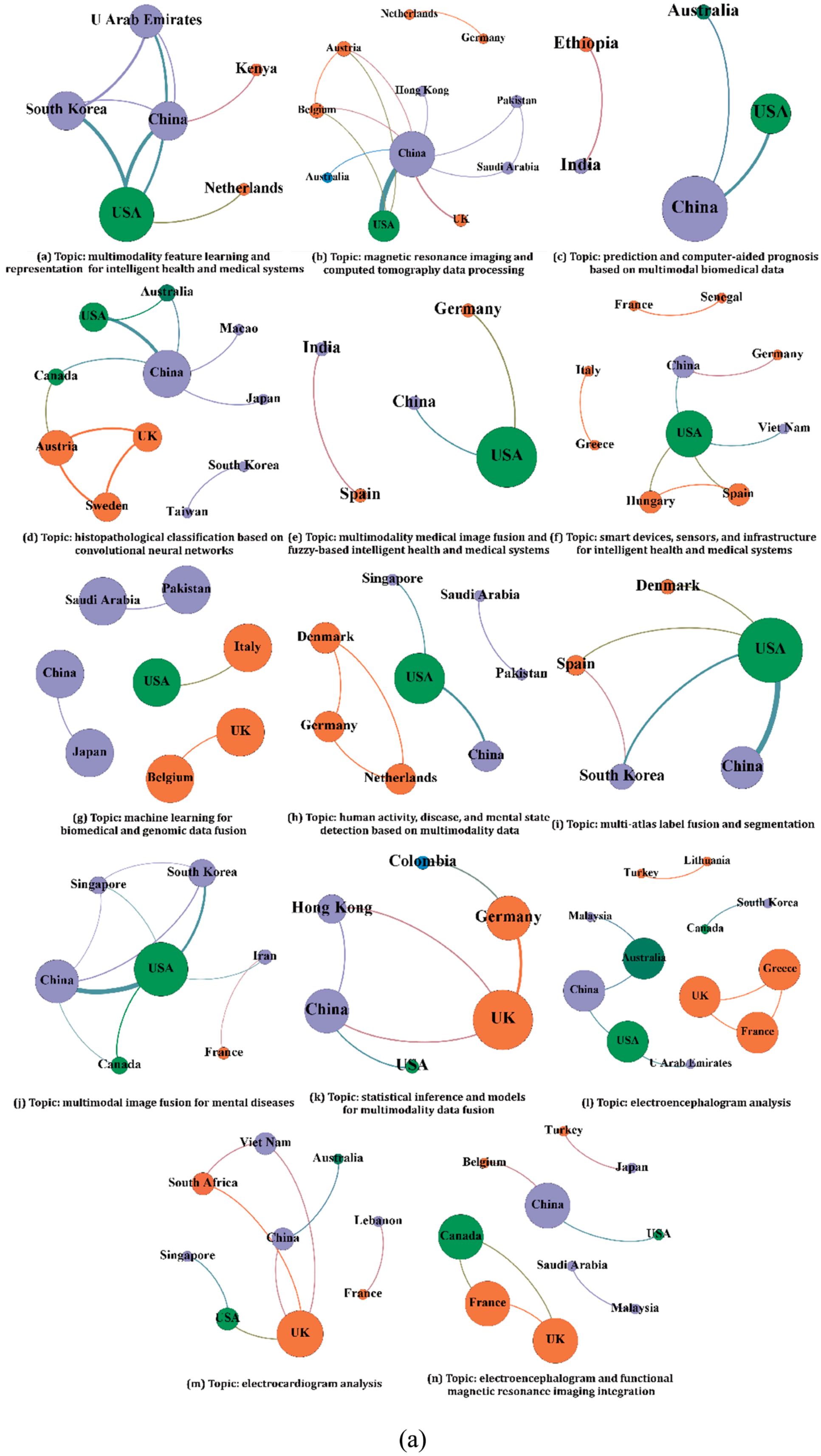
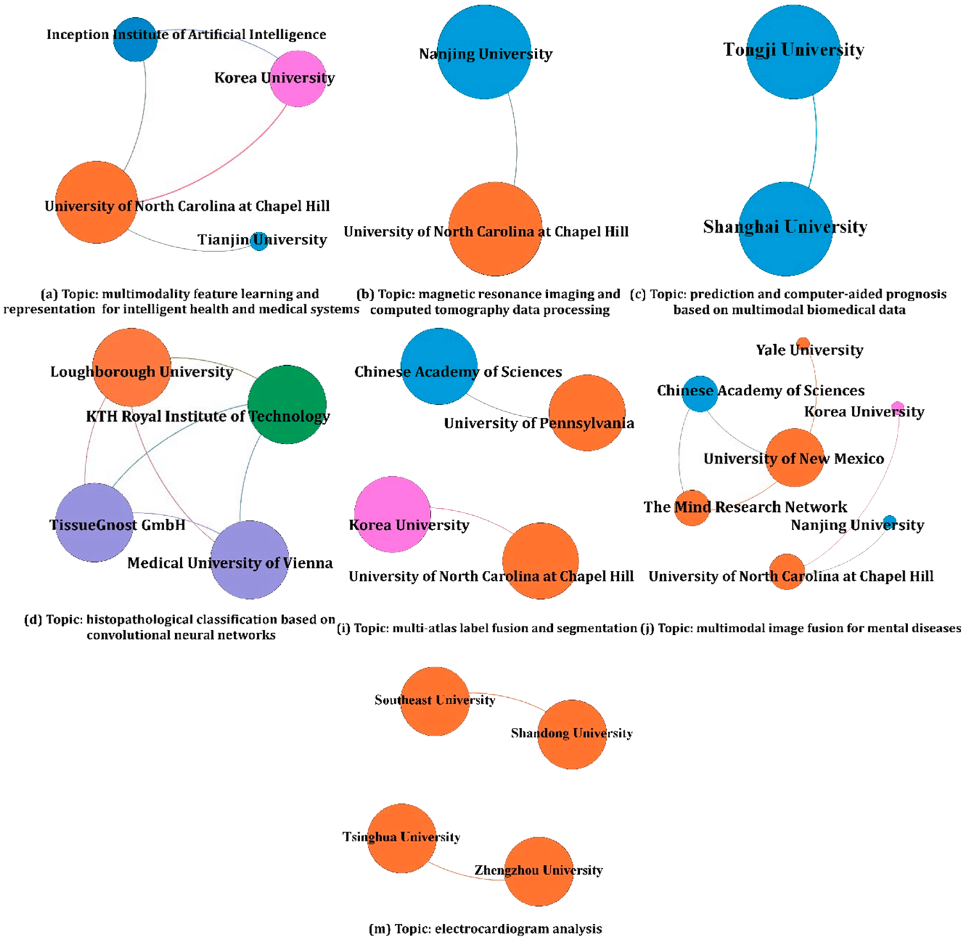


Fig. 14. Collaborative patterns in each topic among countries/regions (a), institutions (b), and authors (c).



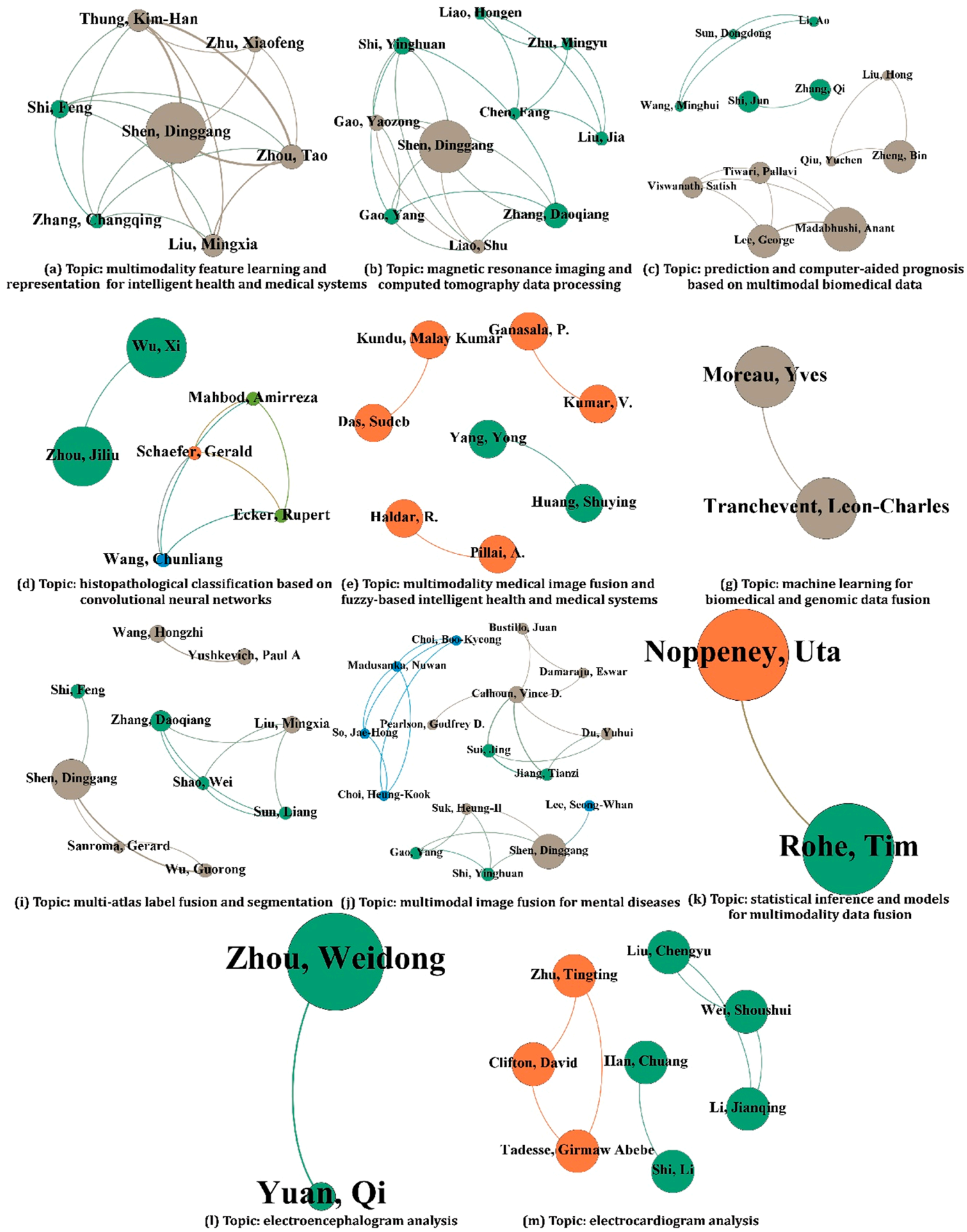
(b)

Fig. 14. (*continued*).

applications that have been successfully adopted for facilitating medical information fusion, the following are worth mentioning.

First, a variety of novel methods for multimodality medical image fusion have been proposed based on fuzzy sets and fuzzy logic technologies. For example, Yang et al. (2018) developed “a novel multimodal medical image fusion method based on structural patch decomposition (SPD) and fuzzy logic technology” (p. 1647). In Yang et al.’s study, SPD was used for extracting salient features for fusion discrimination, and fuzzy logic was employed to construct supplemental fusion maps from salient features. Experiments demonstrated that the proposed approach enhanced fused image details and improved visual effects with only slight differences from source images. Chao et al. (2018) developed “a novel fusion method to combine multimodality medical images based on the enhanced fuzzy radial basis function neural network” (p. 11). They also proposed a hybrid of the gravitational search and error back propagation approaches to train the network to update its parameters. Experiments demonstrated that the proposed approach could synthesize input image information to improve performance efficiently.

Second, feature learning or representation that involves certain technologies such as feature extraction and selection shows effectiveness in disease detection. Feature learning focuses on transforming the multimodal features of neuroimages into abstract representations that are more discriminating and informative through multimodality data fusion (Zhou, Thung, Zhu, & Shen, 2017; Zhang et al., 2020). For instance, Zhou et al., 2019a developed a three-step deep feature learning and fusion strategy for diagnosing Alzheimer’s disease by progressively integrating multimodality imaging and genetic data in each step. The proposed approach alleviated the heterogeneity problem of multimodality data through latent representation learning of varied modalities with the use of an individual DNN model. Experiments indicated the approach’s effectiveness in classification performance with the superiority of adopting multimodality data for diagnosing Alzheimer’s disease. To resolve the problem that the use of merely the intensity features of image patches could not sufficiently depict the appearance of complicated patterns in brain MRIs, Sun, Shao, Wang, Zhang, & Liu, 2019 Sun et al., 2019a focused on multi-atlas driven label fusion, in which high-level features of image patches were retrieved and fused to segment regions-of-interest (ROI) of structural brain MRIs. Experiments indicated the superiority of the proposed approach in ROI



(c)

Fig. 14. (*continued*).

segmentation of brain MRIs.

Third, the big data concept is familiar in medical sciences. Rapid advances in biomedical research, alongside the advent of the big data era, have resulted in enormous amounts of biomedical data, such as genomic data (Phan et al., 2016). The exponential explosion of genomic data brings great opportunities for the elucidation and exploration of the molecular basis of natural variations and human diseases. However, the abundance and complexity of such data also pose particular bioinformatics challenges. There is a call for creating AI-driven data fusion methodologies for improving biomedical decision support, e.g., patient diagnosis, prognosis, and tailored treatment. For instance, An et al. (2019) developed a sequence-driven feature extraction approach, named LCPSSMMF, that integrated local coding with position-specific scoring matrix (PSSM) and multi-feature fusion. Experiments demonstrated the effectiveness of LCPSSMMF in predicting protein-protein interactions. The authors identified three reasons for the success of LCPSSMMF, including local coding based on PSSM, serial multi-feature fusion, and the local average group strategy.

In addition, histopathological image classification, as a subset of medical image classification, is an essential step for providing valuable indicators for disease diagnosis. Automatic and precision classification for histopathological images has great significance in clinical applications. However, such a task is challenging due to dramatic variations in characteristics and representations of heterogeneous features, leading to difficulties for traditional fusion approaches. Thus, classification accuracy still requires improvement before it can meet the needs of clinical applications (Zhang, Dou, Ju, Xu, & Zhang, 2015). Advancements in deep learning have prompted the investigation of its potential for heterogeneous feature fusion in classifying histopathological images. For instance, Yang et al. (2019) adopted a multichannel fusion 3D-CNN (MCF-3DCNN) for the extraction of temporal sequence information and spatial texture information from five-phasic dynamic contrast-enhanced (DCE)-MRIs. Through evaluation, the authors concluded that the MCF-3DCNN was promising for evaluating pathologic grades of hepatocellular carcinoma based on DCE-MRIs.

4.3.2. Brain disorder diagnosis based on multimodality data fusion

The fact that the human brain is complex and current imaging technologies still cannot meet the needs of complete measurement has resulted in the increasing importance of multimodal fusion to "mitigate against misdirection and hopefully provide the key to finding the missing link(s) in complex mental illness" (Calhoun & Sui, 2016, p. 231). Indeed, many studies have investigated using a single modality of a biomarker for brain disorder diagnosis. However, the combination of different biomarkers has been proven to be effective in providing complementary information for disorder diagnosis and increasing classification accuracy in group distinction (Kwon et al., 2019). Therefore, there is a trend in applying AI to improve the diagnosis of brain disorders, particularly Alzheimer's disease and its early stage, for example, MCI, for providing timely treatments or potential interventions (Li et al., 2020a). Evidence has shown that multiple neuroimaging and biological measurements involving complementary information can enhance diagnosis and prognosis. As a result, the combination of multimodal brain imaging data through information fusion can offer rich information for individual subjects through robust multimodal information exploitation (Calhoun & Sui, 2016; Hao et al., 2020a). For example, as a practical matter, subjects' relationships are more complicated as compared to pairwise, and high-order structures with more discriminative information would facilitate classification. Shao et al. (2020) developed a hyper-graph-driven multi-task feature selection approach for classifying Alzheimer/MCI based on a group-sparsity regularizer, a hyper-graph-driven regularization term, and a multi-kernel SVM. Through evaluation, the authors reported that integrating the hyper-graph-driven regularization terms into multi-task learning enabled high-order relations among subjects to obtain discriminative brain regions concerning diseases.

4.3.3. Multimodal neuroimaging fusion

Due to rapid improvements in computing technologies, neuroimaging has dramatically improved the understanding of brain mechanisms and the ability to recognize impairment causes through classifying patients and healthy controls. Moreover, neuroimaging technologies have been regarded as invaluable in neuroscience for visualizing neural activity and identifying biomarkers to make predictions to prevent disease progression.

Neuroimaging involves multiple methodologies, technologies, and noninvasive modalities, such as computed tomography (CT), structural MRI, and diffusion tensor imaging that provide structural and/or anatomical information, as well as modalities, such as EEG, magnetoencephalography, fMRI, PET, and near-infrared spectroscopy, that provide functional information about neural mechanisms.

However, each technology involved in neuroimaging possesses both advantages and disadvantages regarding resolution, safety, availability, and accessibility (Liu et al., 2015). To take advantage of the valuable information about brain structures and activities provided by each modality and compensate for the limitations of individual modalities, researchers have integrated multiple modalities, e.g., multimodal neuroimaging, to elucidate brain dynamics in finer detail. Among multimodal neuroimaging approaches, multimodal data fusion has developed into a scientifically exciting and clinically essential topic and offers significant advantages due to its ability to facilitate true interactions between varied data (Peng et al., 2019; Sui et al., 2014). Multimodal neuroimaging based on machine learning as prognostic or diagnostic tools has become increasingly popular. For example, Phang et al. (2019) developed a deep CNN method for classifying schizophrenia's EEG-based brain connectome. A variety of connectivity features containing time- and frequency-domain metrics of efficient connectivity were combined to obtain complementary information about disrupted connectivity in schizophrenia using a vector autoregressive approach, partially directed coherence and complicated network topology measures. They also designed an innovative multi-domain connectome CNN (MDC-CNN) using a parallel ensemble of 1-D and 2-D CNNs for feature integration from different domains and dimensions through fusion. The authors concluded that MDC-CNN, with the integration of information from varied brain connectivity descriptors, was highly promising for the development of schizophrenia diagnosis applications.

A research tendency for the development and application of symmetrical multimodal EEG/fMRI information fusion approaches is also worth mentioning. Ahmad et al. (2017) developed a machine learning classifier for classifying visual brain activity patterns. The obtained EEG-fMRI data were combined through fusion. Experiments demonstrated the superiority of using simultaneous EEG-fMRI data. The authors thus concluded that the multimodal simultaneous EEG-fMRI method improved accuracy in brain activity pattern classification and was helpful in predicting or fully decoding brain activity patterns.

Furthermore, heart beat detection by jointly analyzing electrocardiogram (ECG) signals and fusing features collected from various signals, for example, arterial blood pressure or morphological and temporal information, are promising for reducing false alarms (Pimentel et al., 2015). For instance, Chen et al. (2020a) designed multi-information fusion convolutional bidirectional recurrent neural networks to detect arrhythmia using ECGs automatically. Moreover, CNNs and bidirectional LSTM were combined for feature enrichment. Experiments showed that the developed approach constituted a promising automatic detection tool that is capable of effectively utilizing both morphological and temporal information in ECGs. In practice, such an approach could be integrated into hardware platforms for clinical arrhythmia detection to aid disease diagnosis. It could also be incorporated into wearable devices to assist telemedicine and home services at Internet hospitals.

4.3.4. Multi-sensor data fusion for smart health

Digital health covers a variety of digital and genomic technologies concerning healthcare, living, and society for the improvement of healthcare delivery efficiency. Recently, there has been a trend in developing smart devices using different technologies, for example, the Internet of Things, intelligent control, and wearable devices (Hsu et al., 2017). The high prevalence of sensors underlying digital health applications has been demonstrated. Moreover, widespread wearable sensors, for example, those in smart watches, have offered "continuous access to valuable user-generated data such as human motion that could be used to identify an individual based on his/her motion patterns" (Dehzangi et al., 2017, p. 1). To date, many researchers have utilized various sensors that are common in our daily lives to detect and recognize human activities of daily living. Furthermore, with the growing interest in using sensor fusion to integrate multiple sensors to extend feature use (Wu et al., 2018), an increasing number of smart health systems that integrate wearable intelligence, AI, and multi-sensor fusion, are available. For example, Wang et al. (2018) designed a recurrent CNN-based approach for hand movement classification. The approach used a deep architecture, which dealt with complicated time-series data like electromyogram (EMG) signals. Transfer learning was adopted to train the multimodal model. Experiments suggested the proposed method's ability in EMG decoding and that sensor fusion could improve myoelectric control systems' performance regarding accuracy and robustness. Dehzangi et al. (2017) presented a sensor fusion approach to identify human gaits by utilizing "time--frequency expansion of human gait cycles in order to capture joint 2-D spectral and temporal patterns of gait cycles" (p. 1). The approach comprised four significant elements, including "cycle extraction, spectro-temporal 2-D expansion and representation, deep convolutional learning, and discriminative multi-sensor model score fusion" (p. 1). Through assessment, the proposed model was found to significantly increase gait identification accuracy.

In robot-assisted surgery, state recognition based on medical imaging and audio signal fusion possesses the potential to make surgical robots more reliable. Sun et al. (2020) developed a state recognition system for robot-aided telesurgery. Robots from the slave-end acted as a surgeon to consider the present operation state and provide informative decision suggestions to facilitate safer telesurgeries. In the proposed system, an audio and force-driven state recognition approach, consisting of signal feature extraction, LSTM-driven prediction, and information fusion strategies, assisted the monitoring of drilling processes by preventing spinal nerve injuries. Indeed, researchers have been working on monitoring surgeon workload during robot-supported surgeries to facilitate task allocation, adapt system interfaces, and evaluate robotic systems' usability. Zhou et al. (2020) focused on user workload prediction during telerobotic surgeries by monitoring surgeons' cognitive load and predicting their cognitive states through wireless sensors. In Zhou et al.'s work, continuous data across multiple physiological modalities (e.g., heart rate variability, electrodermal, and electroencephalogram activities) were recorded and fused using ICA. Results demonstrated that multi-sensors with fusion strategies were superior in predicting cognitive workload levels during complicated surgical tasks. Other researchers have focused on improving human-computer/robot interaction systems' robustness through multiple sensor fusion strategies (Li et al., 2019). For example, Zhang et al., 2020a captured and recognized static and dynamic human gestures in real-time using radial basis function neural networks through a multi-information fusion of flexible strain sensors.

4.3.5. Multimodal biomedical data fusion

With an enormous amount of multimodal, multi-protocol, and multi-scale biomedical data being continually obtained for disease classification, the development of quantitative applications for the combination of information from diverse channels is urgently needed (Viswanath et al., 2017). Information fusion has become prevalent in biomedical data analysis (Rohlfing et al., 2005). Increasing evidence has indicated that application-specific data fusion methods that combine varied sources of biomedical information could improve the predictive value of any modality, suggesting the central role of data fusion in integrated diagnostics and personalized healthcare. For example, Dong et al. (2019) developed a multi-weighted gcForest approach, MLW-gcForest. They implemented a decision-level fusion strategy to facilitate lung adenocarcinoma staging with the use of small-sample multimodal genetic data. Experiments demonstrated the suitability of MLW-gcForest for dealing with high-dimensional, small-sample genetic data and the capability of integrating multimodal genetic data in improving lung adenocarcinoma staging accuracy in comparison to single-modal data. Lei and Fang (2019) developed a novel computational approach, called GBDTCDA, based on machine learning and gradient boosting to predict potential circRNA-disease associations. Through evaluation, GBDTCDA has proven promising for potential circRNA-disease association prediction.

4.3.6. Multi-atlas label fusion

Label fusion constitutes an essential stage in various image segmentation frameworks because it provides "a mechanism for generalizing a collection of labeled examples into a single estimate of the underlying segmentation" (Asman & Landman, 2014, p. 1070). Furthermore, in brain structural segmentation, a multi-atlas strategy is increasingly preferred in comparison to a single-atlas strategy due to its capability of fitting wider anatomical variabilities (Sanroma et al., 2018). Medical image segmentation with multiple atlases has received intense focus because of enhanced robustness against variabilities across varied subjects. An atlas-empowered strategy usually comprises three stages, i.e., atlas selection, image registration, and label fusion (Wang et al., 2012; Zhu et al., 2020). Even though many label fusion methods exist, the majority ignores the higher probability of inner voxels being correctly segmented and the ability of high-reliable voxels to refine the segmentation of low-reliable voxels. To resolve the above issues, Sun et al., 2019b developed an innovative label-spatial reliability-driven robust label fusion approach to segment multi-atlas MRIs. Specifically, original segmentation based on conventional label fusion approaches for targeted images was first performed. Then, for each voxel in targeted images, label, and spatial reliabilities were individually defined based on soft labels and spatial structures from the original segmentation. They further estimated label-spatial reliability for each of the voxels in targeted images. Finally, high-reliable voxels were utilized to refine the label fusion of low-reliable voxels.

4.3.7. Emotion detection and recognition

Emotion recognition, which enables computers to present timely feedback according to humans' emotional states, has been applied in numerous scenarios such as medical assistance and mental health. Diverse physiological signals are imperative for emotion recognition due to the strong relations between physiological reactions and humans. In Wei et al. (2018), a weighted fusion strategy of multichannel physiological signals were used to facilitate emotion recognition by taking advantage of varied signals and decision-level weighted fusion strategies, thus allowing human-like emotion recognition. Researchers in the field of affective computing have focused on multimodal information fusion (e.g., expression, speech, and physiological signals) for data-driven emotion recognition, with higher accuracies obtained compared to single-modal strategies. At present, feature-level fusion strategies are more frequently adopted than decision-level fusion strategies. In the former strategies, feature extraction for each modality is generally realized by using deep learning with dimensionality-reduction approaches, such as pooling and PCA for feature selection and feature dimension reduction, and machine learning classifiers (e.g., SVMs) for model training and emotion classification. In Sahay et al. (2018), feature fusion was realized based on fusing texts, audio, and images using relational tensor networks. In Zhang et al. (2017) and Ma et al. (2019), a deep belief network was adopted to fuse speech and face emotional features, with SVMs for classifying and recognizing emotions. Compared to feature-level fusion, decision-level fusion emphasizes different features' variations. In Gupta et al. (2016), multimodal data (e.g., ECG, EEG, galvanic skin response, and facial expression) were integrated and fused based on the decision-level strategy. In Sun et al. (2015), a weighted product rule was employed for fusing recognition results based on audio and images.

4.3.8. Deep learning-based multi-view fusion

In multi-view learning, information from multiple perspectives is used in object representation enhancement (Wu et al., 2016; Jin et al., 2014). Scholars have increasingly developed diverse multi-view strategies to enhance medical or healthy information fusion and considered multiple networks as multiple "views" of the functional organization of a single brain. Xie et al. (2018)'s study of chest CT images demonstrated the effectiveness of images from multiple views in learning valuable information without the need to introduce redundant information. In Wu et al. (2020), multi-view fusion was integrated into deep learning networks to screen "patients with COVID-19 based on CT images with the maximum lung regions in axial, coronal and sagittal views" (p. 1). Similarly, multiple FCNs possess the potential to enable highly informative representations of the brain's functional organization. Huang et al. (2019) improved the "representation of functional connectivity networks by fusing multi-view information for autism spectrum disorder diagnosis" (p. 833). Hashemi et al. (2020) provided the best adaptation for patients with irregular astigmatism using CNNs based on multi-view Pentacam images.

4.3.9. Automated skin lesion diagnosis

There is an increasing trend in computer-aided skin lesion diagnosis based on precise skin lesion segmentation from dermoscopic images. Various efforts have been made to resolve challenges in anatomical structure learning and skin lesion delineation due to the non-negligible lesion variation in dermoscopic images from different patients. Wang et al. (2019) developed a bi-directional dermoscopic feature learning (biDFL) approach for modeling complicated relationships between skin lesions and informative contexts to attain effective feature representation. Specifically, biDFL was integrated into CNNs to facilitate high-level parsing with a multi-scale decision fusion strategy, which automatically modifies decision reliability. Yap et al. (2018) combined multiple imaging modalities with patient metadata to enhance automatic skin lesion diagnosis using two ResNet-5014 CNNs and a late fusion strategy for feature combination. Afza et al. (2019) automatically detected and classified skin lesions using statistical normal distribution and optimal feature selection, with a probability multiplication law being adopted to fuse segmented images. In Li et al. (2018), "a dense deconvolutional network for segmenting skin lesions" consisted of "dense deconvolutional layers (DDLs), chained residual pooling (CRP), and hierarchical supervision" (p. 527). Specifically, DDLs were used to maintain input and output image dimensions, with DDNs being trained end-to-end without prior knowledge or complicated post-processing processes. The CRP then captured and combined rich local and global contextual information through multi-level feature fusion to obtain a high-resolution prediction.

4.3.10. Fusion strategies based on transfer learning

Traditional approaches for extracting domain-dependent handcrafted ECG features in time- and frequency-domains for disease diagnosis exhibit robustness and generalization deficiencies. To overcome this challenge, Tadesse et al. (2019) adopted a cross-domain transfer learning strategy for classifying cardiovascular diseases based on ECG waveforms, with the utilization of extant vision-driven CNNs to extract features followed by ECG feature learning. Additionally, multiple ECG leads were fused with spectrograms' plausible stacking arrangements for spatial relation encoding. Banerjee et al. (2018) used transfer learning on fused multiparametric MRIs, enabling a rapid, effective, and reproducible rhabdomyosarcoma subtype diagnosis. Such a framework, which efficiently integrates leading-edge image processing approaches based on deep learning, applies to various clinical domains, for example, multimodal imaging for disease diagnosis. Transfer learning has also been widely utilized for skin lesion analysis. Pre-trained CNNs enable deep features to be extracted from fully connected or convolutional layers to train classifiers Mahbod et al., 2019a; Kawahara et al., 2016). Moreover, fine-tuned pre-trained CNNs that replace a network's fully connected layers with new ones (Mahbod et al., 2019), with neurons equaling skin lesion types in number, are effective for classifying skin lesions (Zhang, Wang, Liu, & Tao, 2018; Gessert et al., 2018). Mahbod et al. (2020) demonstrated the effectiveness of multi-scale multi-CNN fusion for skin lesion classification, which integrated the results of various fine-tuned networks trained with cropped images at multiple scales.

4.4. Discussion on the methodologies, limitations, and future work

In this study, to achieve an equitable balance in publication quality and representativeness, only journal articles were included, and conference papers were excluded. The quality of journal articles is generally higher than that of conference papers due to the generally meticulous peer-review process. Secondly, journal articles are popularly adopted to examine research areas (e.g., Chen et al., 2020b;a; 2021a; 2022) with a high level of accuracy and thoroughness being demonstrated. Moreover, conference proceedings commonly involve short papers less illustrative in depicting a research field. Conferences can also vary significantly in publication scale, leading specific conferences to be relatively dominant in the obtained results.

Second, this study did not include data from the most recent two years because a scientific paper requires time to be indexed in an academic database and cited by others. Therefore, the number of papers and citations in recent years is updating (Trinarningsih et al., 2021). Because of this, bibliometric studies commonly would not include recent data to ensure statistical correctness. For instance, Chen et al. (2021b) reviewed papers during the period 1995–2019; Tibaná-Herrera et al. (2018) reviewed papers during the period 2003–2015; Dağhan and Gündüz (2022) reviewed papers during the period 2000–2018. Furthermore, since this study concentrates primarily on the research topics and tendencies, the use of data till 2020 is enough to offer insights into the overall trends and status of information fusion and AI for smart healthcare. Nevertheless, in future work, it would be interesting to add more up-to-date literature to achieve a more comprehensive understanding.

Furthermore, as mentioned previously, in manual data evaluation, many articles were omitted because they were not relevant to health/medical or information fusion. Indeed, they were retrieved through search string sharing by research from varied areas. In future work, it would be valuable to consider search strategy optimization using context-specific queries.

From a methodological perspective, we adopted citation-based bibliometric indicators (i.e., citation count and H-index) to explain journal performance. The results must be interpreted with caution because journals' influence can be impacted by numerous factors, for example, whether a journal is established, new, or inter-disciplinary. This study thus also employed alternative measures, including article count and ACP, for journal measurement from various perspectives. Such a consideration also applies to country/region, institution, and author analyses.

In addition, the present study applied a topic modeling-empowered bibliometric analysis methodology that focuses on analyzing large-scale literature data using automatic machine learning and modeling to identify the popular research topics in the field of information fusion for healthcare with AI. By using the automatic topic modeling methodology, machines can handle large-scale literature data in a very short time; then, the experts only need to evaluate the outputted terms and documents with high possibility and exclusivity to each topic to conduct the labeling task. However, if not running STM but adopting a systematic analysis methodology, experts must manually evaluate each paper in a large data corpus and then summarize the topics, which would be very time-consuming and labor-intensive. Furthermore, the direct subjective evaluation by experts on a large dataset may lead to varied results; however, based on the objective topic modeling results, the summary of topics can be more acceptable as it is derived from both quantitative and qualitative perspectives. In addition, the comparison of the 14 labels derived from topic modeling results can easily reach an agreement; however, it is difficult to reach an agreement when there are hundreds of labels (depending upon the number of publication records involved in the dataset) provided by different experts.

In general, the use of topic modeling methodology compared to systematic analysis methodology contributes to more timely, effective, efficient, and objective results. The experts' evaluation of topic modeling results has also verified its ability to cover most of the topics that domain experts believe are the most important. However, it is always different to cover all aspects in a field due to the problem of topic overlaps and conceptually spurious terms that can result in ignorance of some issues. This is a common problem in topic modeling studies. It is also difficult to cover all aspects in all studies, including those based on direct expert summary using a systematic analysis perspective that involves manual evaluation of a large dataset. As the topic interpretation procedure has been conducted by strictly following previous research, the interpretation results are acceptable. Currently, no study interprets topic molding results without the need for human involvement. In future work, it would be interesting to seek the potential to propose automatic methodologies for interpreting topic modeling results.

Overall, the present study can provide an understanding of the status, trends, and thematic structures of research concerning healthcare information fusion using AI. Nevertheless, it would be interesting to complement text mining techniques with in-depth analysis methodologies, such as systematic reviews, to enable more fine-grained results.

5. Conclusion and significance

To elucidate topics and their evolutions in research about information fusion for healthcare with AI, this paper conducted analyses of scientific literature using STM and bibliometrics. In addition to identifying research frontiers, this study investigated topic dynamics through a non-parametric trend test and identified and visualized topic distributions across significant actors. Analysis of annual scientific output in this interdisciplinary field showed increasing research interest among scholars. Interdisciplinary publication sources linking medical/healthcare and computer science were active in this field. Top productive countries/regions included China, the USA, and the UK, with China contributing to over 40% of the data corpus. Top productive institutions included the University of North Carolina at Chapel Hill, the Chinese Academy of Sciences, and the University of Pennsylvania. International collaborations contributed to better academic performance and faster development. Imaging, multimodal, classification, and segmentation approaches were frequently used in the studied literature. Topics that were frequently mentioned included *magnetic resonance imaging and computed tomography data processing, multimodality medical image fusion and fuzzy-based intelligent health and medical systems, multi-atlas label fusion and segmentation, smart devices, sensors, and infrastructure for intelligent health and medical systems*, and *multimodal image* *fusion for brain disorders*. The research topics *of multimodality feature learning and representation for intelligent health and medical systems, magnetic resonance imaging and computed tomography data processing, prediction and computer-aided prognosis based on multimodal biomedical data*, and *multimodal image fusion for brain disorders*, experienced a statistically significant increase in interest.

This study contributes to the interdisciplinary research field that focuses on information fusion for healthcare with AI. It provides informative and valuable implications, which can assist scholars, policy-makers, and practitioners to more thoroughly grasp the overall landscape and structure of this increasingly important field. The productive actors that are identified can also serve as potential role models and collaborators for researchers. In addition, academic collaborations can be increased and deepened to further investigate the benefits and overcome the challenges of applying AI technologies, particularly those based on deep learning algorithms, to medical information fusion to facilitate optimal decision-making.

The findings obtained provide researchers with actionable insights into decision-making by understanding essential topics in the literature. Increasingly diverse AI techniques, particularly advanced deep learning, have infiltrated medical and health information fusion and demonstrated increasingly promising future development. Further work should extend beyond whether AI technologies could be adopted to support health and medical information fusion, to consider the best ways to integrate various technologies to facilitate effective and efficient information fusion. Particular attention should be paid to the state-of-the-art technologies (e.g., DNNs, CNNs, artificial neural networks, and fuzzy logic) and their combinations with various advanced fusion strategies (e.g., multi-feature fusion, multi-sensor data fusion, multi-atlas label fusion, fusion strategies based on transfer learning, multi-view fusion, and multi-modality data fusion) to enable effective automatic disease diagnosis, support computer-aided prognosis and prediction, build intelligent health and medical systems, and consequently facilitate the development and advancement of smart health.

It is essential to enhance professional and medical experts' confidence and motivation to integrate intelligent systems developed based on AI-driven information fusion into their daily clinical use and during system design. Currently, most systems exist solely as proposals, with little supportive evidence about their effectiveness in real-world practice. Consequently, it is essential to create real-life decision support applications to evaluate their adaptions to realistic diagnosis scenarios and their use as an integral component of clinical instruments. It is highly desirable to involve both data scientists and medical experts in the developmental processes. Indeed, they are essential to identify problems and underlying intricacies to ensure that the AI models work optimally in clinical practice. Moreover, with continuing advancements in AI, it would be challenging to conduct in-depth studies of this field by relying only on computer scientists and medical experts. Thus, close collaborations between researchers and professionals from healthcare, computer science, and others are essential to address the demands and challenges in health and medical information fusion on the road to smart health.

CRediT authorship contribution statement

Xieling Chen: Conceptualization, Methodology, Formal analysis, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Haoran Xie:** Conceptualization, Methodology, Writing – review & editing, Supervision, Funding acquisition. **Zongxi Li:** Data curation, Conceptualization. **Gary Cheng:** Resources, Validation, Supervision, Funding acquisition. **Mingming Leng:** Validation, Supervision, Project administration. **Fu Lee Wang:** Visualization, Project administration.

Declaration of Competing Interest

The authors declare that they have no conflict of interest.

Data availability

Data will be made available on request.

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Supplementary materials

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