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REVIEW

Data visualization in healthcare and medicine: a survey

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Abstract

Visualization analysis is crucial in healthcare as it provides insights into complex data and aids healthcare professionals in efficiency. Information visualization leverages algorithms to reduce the complexity of high-dimensional heterogeneous data, thereby enhancing healthcare professionals' understanding of the hidden associations among data structures. In the field of healthcare visualization, efforts have been made to refine and enhance the utility of data through diverse algorithms and visualization techniques. This review aims to summarize the existing research in this domain and identify future research directions. We searched Web of Science, Google Scholar and IEEE Xplore databases, and ultimately, 76 articles were included in our analysis. We collected and synthesized the research findings from these articles, with a focus on visualization, artificial intelligence and supporting tasks in healthcare. Our study revealed that researchers from diverse fields have employed a wide range of visualization techniques to visualize various types of data. We summarized these visualization methods and proposed recommendations for future research. We anticipate that our findings will promote further development and application of visualization techniques in healthcare.

Keywords Visualization · Healthcare · Electronic health records · Sensor · Omics · Public health · Clinical surgery

1 Introduction

Healthcare sector is undergoing an unprecedented transformation with the rapid advancement of information technology and the widespread application of artificial intelligence. In this revolution, data play a pivotal role. The rapid growth of medical big data aids the optimization and innovation of medical services. It also poses high requirements for data processing and analysis techniques. Data visualization technology, with its intuitive, vivid and easily understandable characteristics, gradually demonstrates immense application potentials in the healthcare field [1, 2].

Data visualization technology transforms complex medical data into easily understandable and analyzable information through visual representations, such as graphics, images and animations [3]. This transformation not only assists healthcare workers in identifying patterns, trends and abnormalities in data but also assists in diagnoses. In addition, patients will have the opportunity to have an intuitive understanding of their health status through data visualization technology, thereby strengthening their capabilities in self-management.

The application of data visualization technology in the healthcare field has become increasingly widespread. It provides medical workers with unprecedented analytical tools. Traditional disease diagnosis methods often have limitations with a single or few indicators. Thus, these methods failed to explain the complex nonlinear relationships that may exist among high-dimensional heterogeneous data. This limitation reflects the inadequacy of human judgment when faced with massive and complex data. The emergence of data visualization technology fills this gap by providing medical workers with a highly intuitive and comprehensive way of presenting information [4]. The support of visualization technology

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can help health professionals in reducing the workload of processing complex data [4]. In genomics research, the diversity and complexity of data make traditional data analysis methods difficult to handle, where thousands of genes, proteins or other molecules exhibit different expression or interaction patterns under various conditions, making the exploration of microlevel domains exceptionally challenging. Visualization technologies, such as heatmaps, scatter plots and network diagrams, allow researchers to interpret these data from different perspectives, thus assisting them in revealing the hidden biomarkers behind the data [5]. Visualization technology also has applications in clinical surgery with tremendous potential. Highly realistic surgical scenarios can be constructed by integrating technologies, such as virtual reality (VR), augmented reality (AR) and mixed reality (MR) thereby enabling doctors to simulate and rehearse surgical procedures before the actual surgery [6, 7]. Developing and applying such visualization scenarios can improve doctors' surgical skills and confidence, as well as providing real-time navigation guidance during surgery, thereby enhancing the effectiveness and safety of surgical procedures [8]. In summary, data visualization technology in healthcare field provides powerful analytical tools for medical workers and healthcare professionals in understanding and effectively responding to complex data. Through data visualization, we can gain insights into the inherent patterns and potential problems within medical data, which aids in improving the quality of medical services.

Despite the promising application prospects of data visualization technology in the healthcare field, it still faces several challenges and issues. Firstly, medical data, encompassing structured and unstructured data, are diverse and complex. Effectively integrating and processing these data is crucial for data visualization. Secondly, different medical scenarios and needs have varying requirements for data visualization, and selecting the optimal visualization techniques based on specific situations is crucial. Thirdly, the interpretability and reliability of data visualization results are important that must be addressed to ensure that the medical staff and patients can understand and use the visualization results in a correct manner.

Therefore, this study aims to provide a comprehensive review of the current research status and development trends of data visualization in the healthcare field by delving into the visualization methods and techniques for different data types. It analyses the application effects and challenges of data visualization in healthcare. Future development directions and improvement measures have also been proposed. We hope that this review provides beneficial references and insights into data visualization research and practice in the healthcare field to promote the comprehensive application and development of data visualization technology in the medical field and contribute to enhance the quality and efficiency of medical services.

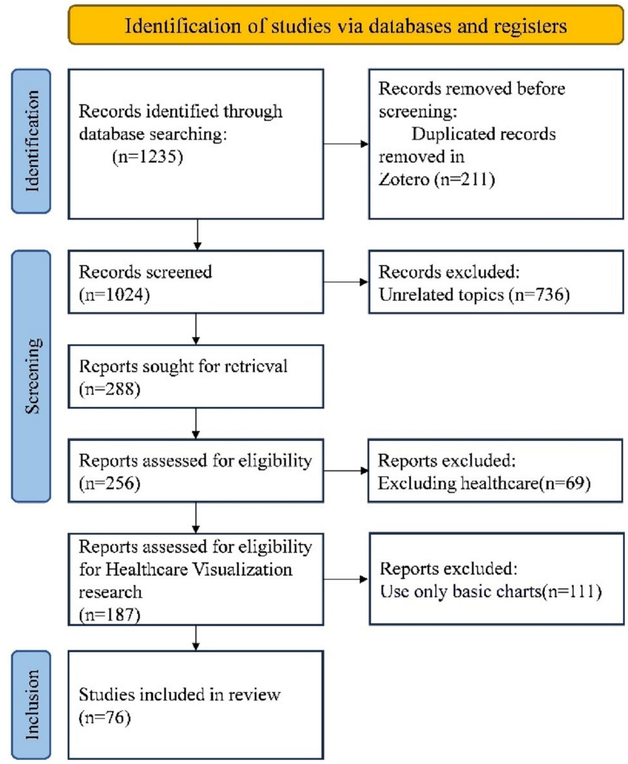

Fig. 1 Flowchart of the study

2 Methods

Literature search strategy and selection criteria:

The inclusion requirements for the literature are as follows: (a) original research articles; (b) published within the past 10 years, including 2014–2024; (c) published in English; and (d) themes focused on the application and research of visualization methods in displaying healthcare-related data. The exceptions for this review include the following: (a) scientific articles published in non-English languages, (b) reviews or editorials, (c) other commentary articles, (d) study of basic charts and graphs based on statistical methods such as line graphs, pie charts, bar charts and scatter plots, (e) duplicate visualization studies in other areas of healthcare and (f) healthcare visualization studies with similar content or subject. To conduct this review, we searched the existing literature, specifically focusing on articles consisting of keywords 'healthcare,' 'medicine,' 'electronic health record,' 'sensors,' 'omics,' 'public health,' 'clinical practice' and 'visualization.' The flowchart for the article review is presented in Fig. 1.

Table 1 Overview of the literature on data visualization in healthcare

Reference	Method or system	Remarks
EHR		
Bernard et al. [24]	dashboards	Visualization of medical history using dashboards
Kwon et al. [16]	RetainVis	Deep learning-based EHR forecasting and visualization tool
Glueck et al. [17]	PhenoLines	A visualization tool for interpreting disease subtypes
Glueck et al. [18]	PhenoBlocks	A visualization system for the diagnosis of hereditary diseases
Trivedi et al. [19]	NLPReViz	Interactive clinical text extraction visualization system
Kwon et al. [20]	DPVis	A system that combines predictive modeling with interactive visualization
Sultanum et al. [21]	Doccurate	Visualization of large clinical text datasets
Guo et al. [26]	EventThread	A visualization system based on event sequences
Gotz et al. [27]	DecisionFlow	A system for analyzing high-dimensional time-event sequence data
Jin et al. [22]	CarePre	Interactive clinical decision support systems
Bernard et al. [28]	visualization system	Interactive data analysis system
Bernard et al. [15]	visualization system	A visual active learning system
Dabek et al. [29]	timeline	A visualization framework system based on event lines
Siirtola et al. [30]	Graphics	A graph-based visualization system for health trajectories
Mayer et al. [23]	ReviewR	EHR data review and entry system
Public health		
Happe et al. [90]	ePEPS	A visualization system for querying and processing patient care pathways
Pachauri et al. [91]	Choropleth Maps	Geographic information-based visualization system for public health
Valdiserri et al. [92]	interactive map	Improving healthcare through interactive visualization maps
Tsoi et al. [62]	Watson Analytics	Visualization of global cancer trends based on Choropleth Maps
Ramadan et al. [67]	interactive map	Visual map-based presentation of breast cancer incidence
Koller et al. [93]	Geographic methods	Geographic methods for health monitoring
Ramadan et al. [94]	interactive map	Visual map-based presentation of breast cancer incidence
Ko et al. [65]	Dashboard	Interactive visualization of prescriptions using interactive dashboards
Henley et al. [66]	Geographic methods	Visualization of case rates based on geographic distribution information
Permana et al. [95]	HAIviz	A visual geographic view system for epidemiological transmission
Mitrpanont et al. [96]	MedThaiVis	Biomedical information visualization techniques

Table 1 (continued)

Reference	Method or system	Remarks
Malakoane et al. [64]	Causal loop diagram	Visualizing Public Health Challenges through Causal Diagrams
Bjarnadóttir et al. [97]	EventFlow	A visualization-based tool to study longitudinal prescribing patterns
Basole et al. [98]	Gephi	An interactive visualization and analysis tool for clinical data
Palmer et al. [99]	network analysis	Exploring referral patterns through data visualization
Alemzadeh et al. [69]	VIVID	Visual analysis of missing values in public health data
Clinical practice		
Kumar et al. [85]	MR	MR-based virtual image reconstruction of faces
Zaman et al. [82]	VR/MR	VR and MR applications in clinical care
Ackermann et al. [70]	AR	AR-based surgical navigation
Condino et al. [71]	AR, virtual X-ray	AR-based surgical simulation training
Liu et al. [72]	AR	AR-based navigation system for hip replacement
Pellegrino et al. [73]	AR	Evaluating head-mounted display AR-based surgical navigation
Logishetty et al. [74]	AR	An AR system capable of tracking bone anatomy
Deng et al. [75]	Tablet-AR	Tablet-AR-based system for neurosurgical navigation
Sun et al. [76]	AR	AR-based surgical navigation system that can be accurately aligned
Adrian et al. [77]	AR	The AR system is used to guide the implantation of surgical devices
Gu et al. [86]	MR	MR-based guidance system for shoulder surgery
Alismail et al. [78]	AR	AR for preoperative tracheal intubation simulation
Gibby et al. [79]	AR, CT	Superimposed AR and CT data for surgical guidance
Sauer et al. [84]	MR-HMD	MR-HMD-based visualization of visceral structures
Kashiwagi et al. [80]	AR	AR-based system for biopsy
Tanbeer et al. [100]	Mivitals	MR system for monitoring vital signs
Jacquesson et al. [101]	3D image	3D glasses-based teaching of anatomical structures
Hussain et al. [81]	AR, CT	Video-based AR surgical system
Yiannakopoulou et al. [83]	VR	VR-based system for surgical training
Cabrilo et al. [6]	AR	AR-based skull base surgery
Cabrilo et al. [7]	AR	AR-based bypass surgery

Table 1 (continued)

Reference	Method or system	Remarks
Jia et al. [8]	AR	AR-based surgical assistance system
Omics		
Herzinger et al. [5]	tranSMART	The system includes interactive heatmaps, volcano maps, box diagram, etc.
Bolouri et al. [48]	clustering graph	Cluster analysis visualization to distinguish patient groups
Zhu et al. [52]	NetGestalt CRC	The site provides querying, integration and visualization of omics data
Ghosh et al. [53]	multiSLIDE	Quantitative multi-omics data interpretation and visualization
Hernández et al. [54]	PaintOmics 3	Multi-omics data visualization platform
Dabdoub et al. [55]	PhyloToAST	High-dimensional data visualization and analysis
Nishida et al. [57]	transomics2cytoscape	Multi-omics-biochemical network visualization techniques
Brich et al. [58]	visMOP	High-throughput methods for visualizing multi-omics data
Goldman et al. [51]	UCSC Xena	Lightweight genomics visualization platform
Sensor		
Kim et al. [41]	Data@Hand	A visual exploration system supporting multimodal interactions
Meyer et al. [102]	time-based	Mobile health data visualization
Khan et al. [103]	IoMT-based	A visualization system for remote patient monitoring based on IoT technology
Arcia et al. [104]	infographic	An infographic to promote healthy understanding
Schneider et al. [105]	Virtual Item View	Visualization of personal data using the virtual item view
Polack et al. [45]	Chronodes	Visualization System for Longitudinal Analysis of mHealth Data
Turesson et al. [106]	SWEPPE	An interactive visualization system to support chronic pain patients
Aslam et al. [46]	InfoFramework	Capturing personal conditions based on mobile sensing technology
Ledesma et al. [107]	hFigures	Graphical representation of personal health data application
Faiola et al. [108]	HYPOalert	Supports testing and visualization of blood glucose management systems
Aida et al. [109]	MIRAMED	A mobile video health service based on mHealth
Serhani et al. [110]	SME2EM	End-to-end disease surveillance system
Wang et al. [111]	space–time	A visualization system for prompting sedentary behavior
Yi et al. [40]	TransPose	Real-time human posture estimation

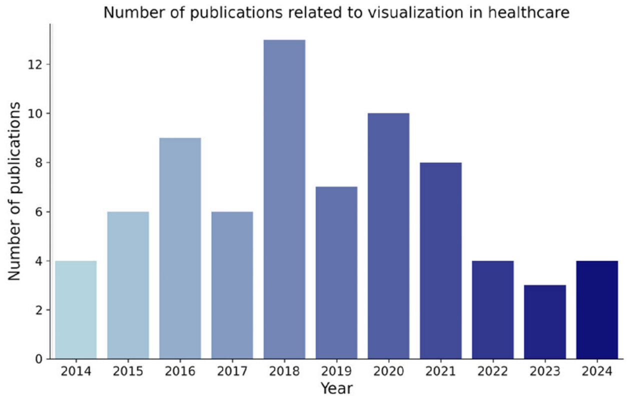

Fig. 2 Number of publications related to visualization in healthcare per year

3 Results

In this study, the categories are classified based on Dash's classification method [9], which consists of five main categories: electronic health records (EHR), sensors, omics, public health and clinical practice. This section elaborates on the data visualization content in each category separately. Table 1 demonstrates the number of studies included in the different category areas and the reference index. Figure 2 shows the number of related publications published per year. Figure 3 shows the different categories of content involved in this study.

EHR has a wide range of data types covering a variety of different structures. This study identifies two main approaches to EHR data visualization based on the literatures: one based on machine learning and deep learning and the other based on the sequence of events.

Due to the rapid development of sensors and mobile devices, there has been a lot of research on the application of sensors in healthcare. The types of data collected by sensors can be categorized into motion data and somatic data. Due to the homogeneous and structured nature of the somatic data, most of the studies can be presented with just basic charts. Visualizations based on motion data are usually processed in a deep learning manner and presented through predictive models. This study also explores research on mobile visualization applications and how users' understanding can be improved through improved interactive visualizations (Fig. 3).

Omics data visualization methods are relatively fixed and mainly include heatmaps, network diagrams, Manhattan diagrams, etc. Different charts are used to demonstrate specific data types and expression needs. Therefore, this study focuses on the visualization systems in different subdomains. Visualization methods in public health include basic charts, Choropleth Maps, and time-series analysis.

Visualization of clinical surgical scenarios mainly consists of VR, MR and AR systems. Among them, VR systems are mainly oriented to clinical practice and training. AR and MR systems are used for clinical surgical practice.

3.1 Visualization of EHR

In the healthcare field, doctors face immense work pressure and time constraints. Thus, they urgently need effective decision support tools to assist them in making efficient and accurate clinical decisions. Despite significant advancements in information technology, doctors are still reliant on manual approaches to interpret numerous medical records in their daily work, undoubtedly increasing their workload. This situation is particularly prominent in developing countries and has become a critical factor limiting the capabilities in improving the quality of medical services [10]. Therefore, enhancing the visualization level of the medical system while providing doctors with highly efficient and convenient auxiliary tools has become an urgent issue that needs to be addressed in the current field of medical information visualization. As an electronic carrier of patient medical information, an EHR provides strong support to address the aforementioned issue with its patient-centered design concept. EHRs contain patients' medical and treatment history records and cover a wide range of patient care information, such as medical history, diagnosis, medication, treatment plans, immunization dates, allergy information, radiological images and laboratory test results [11]. This complementary information enables doctors to deeply understand patients' health status and make highly accurate diagnoses and treatment decisions. Additionally, EHR's real-time updating feature ensures that doctors can access the latest medical information for patients at any time. Therefore, as an essential component of smart healthcare, EHR provides doctors with a comprehensive, real-time and secure patient information recording system and helps optimize the workflow of doctors and nurses, thereby improving the quality and efficiency of medical services. Given the continuous improvement of medical informatization, EHR will play a crucial role in future medical practice.

Iakovidis defined EHR as the digitized healthcare information of individual patients; it is accessible, secure and highly available to support healthcare, education and scientific research [12]. The EHR system can comprehensively analyze the patient's entire cycle of medical treatment status, thereby providing strong support for clinical decision-making [13]. The widespread adoption of EHR has enabled the medical field to accumulate a large amount of clinical data. These data include structured biological results, diagnostic codes and unstructured text data. EHR is typically composed of diverse and heterogeneous data, with a large scale and varying data quality [14]. The effective utilization

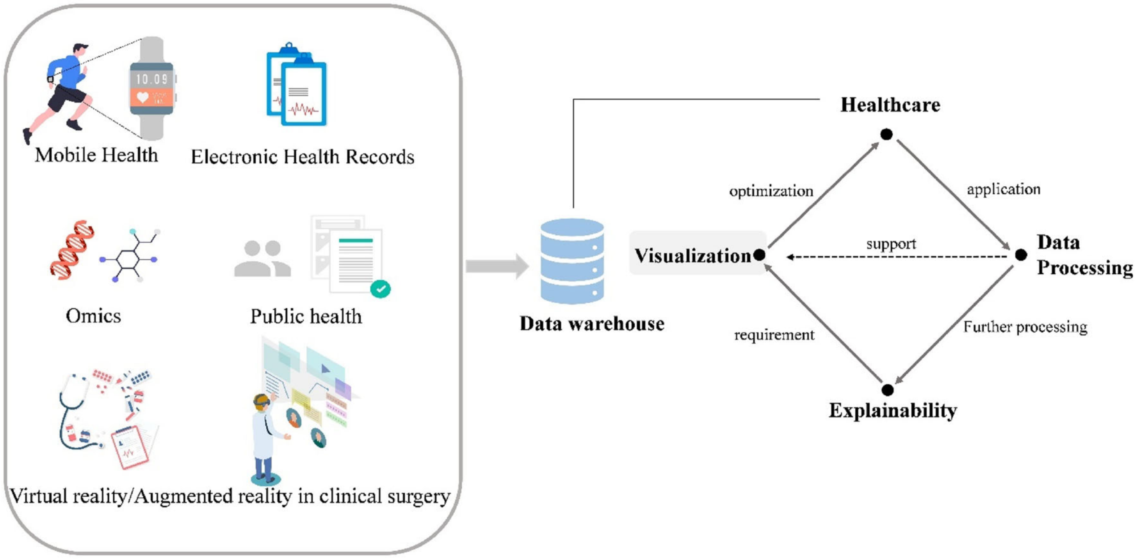

Fig. 3 Healthcare data processing and visualization flow diagram

of these data remains an urgent challenge that needs to be addressed. Therefore, EHR can be improved and optimized through information visualization techniques, such as adopting appropriate layouts, visual encodings and interactive tools, to enhance further the decision-making effectiveness of medical staff. Current visualization research has two main parts; the first part uses machine learning or natural language processing [15–22], and the second part is mainly based on events [23–30]; these techniques enable these data to be transformed into valuable medical information [31].

Researchers frequently use machine learning methods to gain deep insights into patients' conditions [2], such that the underlying patterns of disease progression from long-term health records can be revealed. An effective method involves using a limited number of states to describe different disease stages of patients. These states reflect the different distribution characteristics that patients present on a series of medical indicators. Hidden Markov models and their variants are suitable tools for such research. They can help to discover these states and infer patients' current health status. On the basis of the above ideas, Kwon et al. developed a system named DPVis [20]. This system can seamlessly integrate the parameters and results of the hidden Markov model into an easy-to-understand and interactive visualization interface. This study showed that the system can effectively evaluate disease progression, visually summarize different disease states and allow researchers to explore patterns of disease progression interactively. This system can also construct, analyze and compare clinically meaningful patient subgroups. Jin et al. developed the CarePre clinical decision support system, which can visualize EHR records while predicting disease states [22]. The system extends state-of-the-art deep learning models to predict adverse medical events based on patients' historical medical records. The system includes an intuitive interactive framework designed to support diagnostic and treatment outcome analysis. The study demonstrated the effectiveness and practicality of the CarePre system through case studies and interviews with senior doctors and pulmonologists.

Clinicians often record patients' physical conditions through various textual methods. This recording process may require appropriate modifiers to capture words, phrases and their relationships in EHR. NLP can convert a large amount of unstructured text in EHR into a structured and machine-readable format. It may also require suitable modifiers to capture words, phrases and their relationships in EHR. Wang et al. used NLP to model EHR data [32]. Sultanum et al. developed a system named DocCure, which allows users to visualize large clinical text datasets [21] and provides clinicians with customizable automated auditing techniques while maintaining the ability to link to the original text. Trivedi et al. introduced NLPReViz, a clinical EHR visualization analysis tool based on machine learning and NLP [19].

Besides the above methods based on machine learning and deep learning, EHR visualization analysis can be presented using the statistics of events at different time points. This approach can capture the core elements of medical events, thereby improving the effectiveness of EHR data processing and visualization. It has been adopted by multiple EHR visualization systems [33]. Visually exploring sequences containing numerous events or sequences with many types of events is a challenge. Current methods mainly use statistical analysis to identify event patterns and depict the stages of event development over time. Guo et al. proposed a visualization system named EventThread, which innovatively utilizes tensor analysis techniques to cluster complex event sequences into clear threads [26]. These threads can show the potential stage categories of events and reveal the evolution patterns of events. EventThread allows users to group threads interactively based on similarity to observe clusters intuitively at specific time points. Researchers applied EventThread to three application scenarios to verify its effectiveness. They also invited experts for practical experience and interviews. The results showed that EventThread can effectively help users in understanding and analyzing event sequences with strong practical value [26]. Bernard et al. developed an innovative visualization technique that does not simply treat patients' medical histories as a series of raw events; in particular, this technique segments patients' medical histories. This technique aggregates the entire medical history or treatment process. After that, the aggregated segments are transformed into intuitive static dashboards for display, which are then orderly arranged in a dashboard network for better presenting the longitudinal changes in patients. Researchers invited five nonexperts, five visualization experts and four medical experts to evaluate and validate the effectiveness of this system. The results showed that experts managed to use the system to quickly overview a large dataset containing 2000 patients. Moreover, longitudinal changes and differences between different cohorts could be easily observed, which demonstrated the great potential of dashboard visualization in presenting staged changes in large-scale data [24].

3.2 Visualization of sensor data

In the healthcare sector, sensor-based technology can be used to collect health information from patients or users. Sensor data exhibit diversity, with the main types of collectible data including physiological and motion data. Physiological data, the most common type of sensor data, encompass body temperature, heart rate, blood pressure, blood oxygen content and respiratory rate [34]. These data are typically collected by wearable devices or clinical monitoring equipment for real-time monitoring of patients' physiological states. Motion data are primarily collected through sensors, such as accelerometers and gyroscopes, built into mobile phones or sports watches. These sensors capture users' motion states, including step count, walking distance and physical activity level. Such data are crucial for assessing patients' recovery progress and daily living abilities [35].

Mobile health (mHealth) is one of commonly used applications that utilizes mobile technology to acquire health-related data and support medical services [36]. With the rapid development of mobile sensor technology, it is now possible to better understand the patterns and associations of physiological factors. Using these hardware and software technologies, researchers now can collect and analyze users' health data more accurately and quickly than ever before. However, visualizing these data efficiently and intuitively remains a challenge. Considerable research has been made on mHealth with the underlying aim to improve user health through mobile technology. However, one of the challenges lies in presenting the results of mobile data in a clear, understandable and intuitive manner.

Motion data are primarily collected through sensors, such as accelerometers and gyroscopes, built into smartphones or watches. These sensors generate specific types of signals during measurement and recording [37]. Accelerometers are commonly used to measure the acceleration of objects and may produce data on changes in velocity. The specific form of the data may vary depending on the type of accelerometer, such as open-loop or closed-loop, piezoelectric, piezoresistive and potentiometric. Gyroscopes are primarily used to measure or maintain direction. They obtain information on motion status by measuring the angular velocity or angular displacement of an object around a certain axis. An effective approach to visualize these two types of data involves selecting appropriate chart types. For instance, line charts are suitable for displaying trends; therefore, they can be used to show changes in acceleration over time. Bar charts are highly suitable for comparing data from different categories, making them useful for comparing acceleration magnitudes in different directions or on different axes. Pie charts, which are used to show proportional relationships, may not be the preferred choice when analyzing the composition of accelerometer or gyroscope data. Apart from the direct visualization of raw data, machine learning or deep learning methods are explored by researchers to identify various states of users during motion and represent them in various forms. For instance, several studies have aimed to recognize users' motion states and patterns through mobile sensor data [38, 39]. Although this approach typically involves textual descriptions of users' motion patterns, it enhances the expression of abstract motion data. Yi et al. achieved a visual representation of human motion postures by attaching six small sensors to users, enabling real-time motion capture and visualization [40]. This study divides the motion capture process into three subtasks: Firstly, the positions of the five main nodes (head and limbs) are calculated from inertial data, secondly, the positions are refined into 23 nodes throughout the body, and finally, the spatial positions of each limb are located by inverse dynamics. Given that predicting human motion requires data from before and after the current moment, a bidirectional recurrent neural network was used for training. The above visualization technique, which is based on motion sensor data, helps healthcare professionals obtain timely information on users' daily motion and status. It also enables the derivation of many health-related outcomes from raw data. Thus, it can facilitate remote diagnosis and medical assistance for users.

In addition to motion sensors, such as smartphones or sports watches, various sensors record physiological data and can capture multiple physiological parameters. The commonly used physiological data sensors are temperature sensors, heart rate sensors, heat flux sensors, electrocardiographic sensors, electroencephalographic sensors and optical sensors. Temperature sensors monitor body temperature in real time. Heart rate variability sensors, primarily through contact with the skin or wireless transmission, can capture real-time heart rate data. They aid in cardiac function and exercise status assessments. Heat flux sensors can be used for auxiliary calculation of blood glucose levels and estimation of metabolic capacity. Bioelectric sensors can be used for electrocardiogram (ECG) and electroencephalogram (EEG) data acquisition, as well as for fat content estimation. Optical sensors can calculate blood oxygen levels and blood flow rates. The data obtained by these sensors can be primarily classified into analog and digital signals. Analog signals, such as ECG and EEG waveforms, provide rich physiological information, and their visualization methods are similar to those described in the previous section for motion sensor signals. Digital signals are represented as binary sequences of numbers. Such data can be directly processed, stored and transmitted. Visualization of digital signals is relatively straightforward. For instance, step counts and other data can often be represented using bar charts [41]. Line charts can be used to display emotions, weight, heart rate, blood pressure and sleep patterns. Bubble charts are commonly used to visualize weight, food intake and blood pressure data. Pie charts are often employed to show weight distribution, blood pressure, sleep patterns and blood glucose levels. Radar charts are used to display sleep data, and heatmaps are utilized to represent emotions, step counts and food types [42, 43].

In addition to the aforementioned visualization methods for raw sensor data, systems that deviate from traditional visualization techniques have been developed by numerous researchers to enhance the expression and interaction of mHealth data, thereby improving user experience. Current research has summarized the approaches to data visualization in the mHealth field, and the primary focus includes bar charts, pie charts and the combination of textual summaries and charts [44]. Developed by Polack et al., the Chronodes system is an interactive platform that integrates data mining and human-centered visualization techniques to provide deep analytical support for longitudinal mHealth data [45]. This system efficiently extracts and visually presents frequently occurring event sequences, thereby revealing hidden activity patterns of participants across multiple time axes. Furthermore, Chronodes incorporates innovative interaction techniques and visualization methods to analyze multifocal events sequentially. This feature allows health researchers to define, explore and compare different behavioral groups interactively through combinations of event sequences. A pilot study involving 20 biomedical health experts was thoroughly summarized to delve into the practical efficacy and potential impact of Chronodes in the mHealth domain. The study showed that the system not only enhances the efficiency and accuracy of health research but also provides powerful technical support and theoretical guidance for future studies. Aslam et al. developed a mHealth data visualization application based on Android architecture [46]. This framework aims to obtain user activity status and well-being data through mobile sensing technology and present these data visually, thereby enhancing users' self-awareness. The system successfully achieves comprehensive monitoring of individual behaviors and habits. The study developed a set of lightweight interactive visualization tools that effectively summarize and present quantitative data related to user behavior patterns and habits. Users can visually understand their behaviors and habits through this approach, enabling self-monitoring and reflection after actions.

3.3 Visualization of omics data

In the field of life science, data undoubtedly serve as a critical driving force for scientific research progress. The rapid development of high-throughput technologies has enhanced data acquisition efficiency and precision. However, these technologies exhibit complicated data processing requirements. Extracting valuable information from vast amounts of omics and clinical data has become a significant challenge in the life science community. As an intuitive and effective data processing tool, information visualization techniques gradually emerge as a key solution to this challenge. Researchers can gain a highly intuitive understanding of the inherent patterns and connections within the data by transforming complex data into visual forms, such as graphs and images; this approach can help them discover new research clues and directions [47].

Various information visualization methods and techniques have been widely applied in various fields of life science. These methods not only aid researchers in quickly browsing and screening data but also reveal complex relationships and patterns in the data. For instance, heatmap-based visualization methods can be used to display changes in gene expression profiles, whereas network diagrams can help reveal protein–protein interaction relationships [48]. With the continuous development of technology, an increasing number of software tools have begun to support the application of these visualization methods [49]. These tools provide rich visualization options and interactive functions. They can also be seamlessly integrated with data analysis tools, thereby providing users with a complete data analysis workflow. Despite the achievements made by the application of information visualization methods in life science, many challenges and issues still need to be addressed, such as selecting the appropriate visualization method based on specific research needs, effectively interpreting and communicating visualization results and integrating these methods effectively into existing research processes.

The deep exploration of the omics field has made the development of computational methods that can effectively analyze and interpret complex data crucially. This domain not only integrates knowledge from multiple disciplines, such as computer science, chemistry, bioinformatics and medicine, but also stands at the intersection of these disciplines, thereby forming a highly interdisciplinary research area [50]. The primary research goal of this field is to use advanced computational, statistical and machine learning methods to explore deeply inherent patterns and to derive useful findings from the omics data. This field also strives to integrate these data organically with other clinical data. This comprehensive analytical approach helps reveal the underlying mechanisms of biological processes. It also provides new ideas and strategies for disease diagnosis, treatment and prevention. Therefore, omics research based on the development of multiple disciplines holds profound significance for promoting the progress of the entire life science field. This section primarily focuses on the visualization research of omics in the healthcare domain. Figure 4 illustrates the basic research process of omics and the widely adopted visualization methods.

Given the advancements in omics technologies, such as large-scale parallel sequencing and mass spectrometry analysis, multi-omics analysis has increasingly become a core approach in cell biology research and clinical applications. However, the analysis of multi-omics datasets poses significant challenges. These challenges stem from the continuous expansion of data dimensions and the complexity introduced by the interconnectedness among multiple high-dimensional datasets. In traditional omics data analysis pipelines, data analysis often relies on the application of statistical filters or abstraction by projecting data into low-dimensional spaces for visualization and interpretation.

Currently, various visualization methods are available in the field of omics [5, 48, 51–58]. This section presents several representative examples. Developed by Gao et al., cBioPortal provides a method for exploring and analyzing multidimensional cancer genomics data. This system can optimize the molecular profiling data of cancer tissues and cells, enabling a deep understanding of genetic, epigenetic, gene expression and proteomic events. It allows interactive exploration of variations among samples, genes and pathways, and these variations are connected with clinical outcomes. The system offers multiple functions, including network visualization analysis, survival analysis and patient-centered queries. This study also provides guidelines for the analysis and visualization functions of cancer genomics [59]. UCSC Xena, developed by Goldman et al., is a tool specifically designed for visualizing and analyzing large datasets to address the challenges posed by the growing size and increasing complexity of the current and future data. Its unique software architecture enables cancer researchers to explore vast and diverse datasets easily, regardless of their computational background. Researchers can securely analyze their data using this system parallel with public data or independently, ensuring the security and privacy of private data. The system exhibits excellent scalability, can easily support the analysis of tens of thousands of samples and has been validated in tests involving one million cells. Furthermore, its simple and flexible architecture provides robust support for various common and uncommon data types. Xena's visual spreadsheet function integrates views of multiple data modes, such as gene-centered and genomic coordinate-centered views, thereby providing researchers with a comprehensive visual representation of genomic events in tumor cohorts [51].

The field of data analysis is facing unprecedented challenges with the increasing popularity of multi-omics platforms. The joint visualization of multi-omics data is particularly important to understand the complex interactions between molecular layers, to fully utilize the multi-omics resources and to promote biological discoveries. PaintOmics 3, developed by Hernández-de-Diego et al., is a web-based visualization tool designed to enable the integrated visualization of multiple omics data types on the Kyoto Encyclopedia of Genes and Genomes pathway maps [54]. PaintOmics 3 innovates in combining server-side functionality for data analysis with advanced techniques for network data visualization. Thus, it can provide researchers with a powerful interactive platform to explore multi-omics information. Compared with other visualization tools, PaintOmics 3 offers a comprehensive workflow for pathway analysis, including name/identifier conversion, multi feature matching, pathway enrichment analysis, network analysis and interactive heatmaps and trend plots. Additionally, PaintOmics 3 is compatible with various omics data types, such as transcriptomics, proteomics and metabolomics. It also supports region-based analysis methods. Biologists have long history of using biological pathways to describe the detailed steps in biological processes. These powerful visual representations can effectively aid researchers in understanding, sharing and discussing knowledge.

Network-based analysis techniques possess significant advantages. Thus, they enable a deep dissection of multilevel omics information, such as somatic mutations, copy number variations and gene expression data, thereby revealing profound biological insights. However, this comprehensive analysis process is extremely complex and difficult to achieve through simple automation. Therefore, the development of

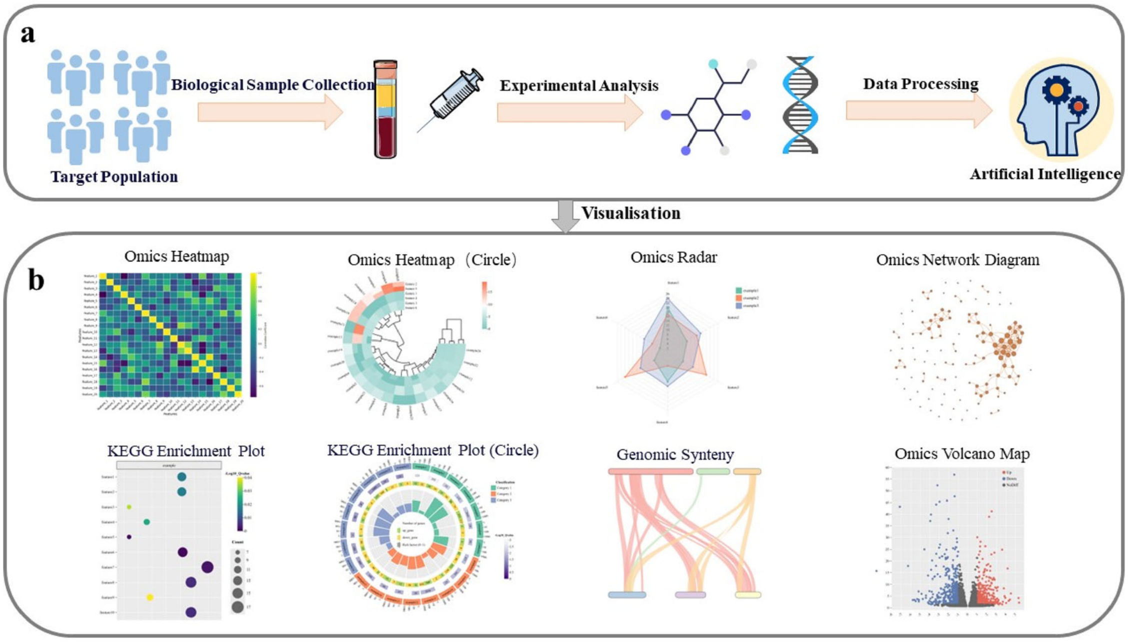

Fig. 4 Schematic diagram of omics data including acquisition, processing and visualization. **a** Acquisition and processing of omics data. **b** Visualization methods of omics data mainly include heatmaps, radar charts, network diagrams, enrichment plots, gene collinearity maps and volcano plots

interactive visual mining tools is particularly important as they will aid in identifying driver genes and regulatory modules, thus allowing us to better understand biological systems. Developed by Jang et al., MONGKIE has achieved a deep integration of network visualization with omics data analysis tools, thereby providing users with a comprehensive and efficient set of analytical tools [60]. In terms of visualization, the platform offers diverse options for presenting multi-omics data and introduces unique network models to depict complex biological network structures, such as interactions between biomolecules. Additionally, the platform integrates various internal network analysis algorithms, including network clustering, further enriching its analytical capabilities. The platform boasts novel features, such as the simple definition of subgroups and optimized visualization, thereby facilitating users' intuitive understanding of data structures and inherent relationships. Moreover, users can compare and analyze multiple datasets within the same network through data-to-visual mapping and subsequent overlay functions, thereby allowing to reveal the dynamic changes in biological networks. This study conducted a deep analysis using the Cancer Genome Atlas glioblastoma data to validate the practicability of the platform. The results demonstrated that MONGKIE has an excellent performance in network-based multi-omics data visualization and mining. In addition, as the system is developed with the Java environment and the NetBeans plug-in architecture, which provides strong compatibility with different system environment. Moreover, its open architecture facilitates module expansion for third-party developers, further enhancing its application potential. Cytoscape, developed by Shannon et al., aims to integrate biomolecular interaction networks with high-throughput expression data and other molecular states into a unified conceptual framework [61]. Cytoscape provides a series of basic functions, including network layout and querying, as well as the visual integration of networks with expression profiles, phenotypes and other molecular states. Additionally, it supports linking networks to databases of functional annotations, thereby providing users with highly comprehensive information. The case studies conducted for applying Cytoscape cover various fields, such as identifying pathways associated with changes in gene expression, studying protein complexes involved in cellular DNA damage repair and constructing interfaces for detailed kinetic gene regulatory models. These cases showcase the widespread application of Cytoscape in the field of bioinformatics and validate its powerful data processing and visualization capabilities.

3.4 Visualization of public health data

Various methods of data visualization are used in the field of public health. They are primarily determined by the type of data and analytical requirements. The following are some common methods for the visualization of public health data. Two-dimensional scatter plots are used to compare the

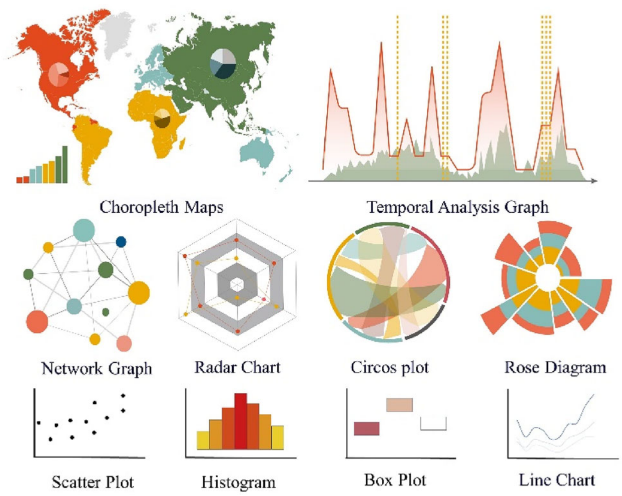

Fig. 5 Schematic diagram of data visualization methods in public health field

relationship between two variables, for instance, the correlation between age and disease incidence. Choropleth maps primarily distinguish data from different regions through colors, sizes or other visual elements; they are often used to demonstrate the geographical distribution or transmission of diseases [62]. Temporal analysis charts, mainly including line charts or bar charts, exhibit data that vary over time, such as the trend of disease incidence over time [63]. Spatiotemporal exploration analysis combines spatial and temporal dimensions to analyze the spread and propagation of case examples. This approach can help reveal the transmission patterns and paths of diseases. Apart from the aforementioned common methods, tree diagrams can be utilized in public health data visualization to analyze hierarchical data, such as disease classification or transmission routes. Simultaneously, some complex public health data may require additional methods for processing and presentation [64]. This section focuses on visualization methods for Choropleth Maps, time-series analysis and special needs. Basic charts based on traditional statistical methods for data processing (scatter plots, line graphs, bar charts, pie charts, etc.) are not explored in depth. Examples of Choropleth Maps, time sequence analyses and basic diagrams are shown in Fig. 5.

In practical applications, visualization teams typically embark on their work encompassing data mining, data analysis, logical architecture, visualization representation and development, among others. They comprehensively apply various visualization methods to present and analyze public health data. Additionally, an increasing number of visualization tools and software for public health data, such as Tableau, have been developed with the advancement of technology [65]. These tools offer diverse visualization techniques and robust data processing capabilities. Thus, they can facilitate data analysis and decision support in the field of public health.

The visualization method of public health data based on choropleth maps is an intuitive and effective technique to display public health data's spatial distribution and differences. This method primarily utilizes colors, sizes or other visual elements on maps to distinguish data levels or categories in different regions, thereby assisting users in quickly understanding and analyzing the spatial characteristics of public health data. The following are the main steps involved in visualizing public health data based on choropleth maps. (1) Map selection: An appropriate map type, such as world maps, national maps and regional maps, is selected based on the spatial scope and granularity of the data. The resolution and detail level of the map must be considered to ensure an accurate representation of the spatial distribution of data. (2) Data classification: The data are classified into different levels or categories based on their range and distribution characteristics. This step can be achieved by setting thresholds, using clustering algorithms or employing other statistical methods. The purpose of classification is to transform the data into visually distinguishable hierarchies and demonstrate spatial differences in the data effectively. (3) Map drawing: Professional visualization tools or programming languages (such as Geopandas library in Python or ggplot2 package in R) are utilized to map the data onto the map and assign different colors, sizes or other visual attributes to different regions based on data classification. For instance, color shades can be used to represent the level of disease incidence; alternatively, sizes can be employed to indicate the number of infections.

Kelvin et al. collected cancer data from 100 cancer registries worldwide provided by the World Health Organization to analyze the inherent patterns of global cancer incidence rates [62]. The authors constructed a visual analysis platform based on IBM Watson Analytics to achieve the objective mentioned. This platform can process and analyze cancer data from 26 types of cancers across eight diverse geographical regions, including the USA, the UK, Costa Rica, Sweden, Croatia, Japan, Hong Kong and China. The research team utilized the platform to create choropleth maps, which visually represent the spatial distribution characteristics of cancer globally. Additionally, line charts were generated to reveal the historical trends of cancer incidence rates over a 29-year period. Furthermore, subgroup analyses were conducted for different age groups to analyze age-related differences in cancer incidence rates comprehensively. This visual analysis platform offers real-time interactivity, allowing users to select specific cancer types, genders, age groups or geographical regions easily for further data exploration. As a cloud-based platform, the teams' visual analysis platform efficiently handles vast amounts of data and can be accessed by any device with an Internet connection. As a result, the convenience and flexibility of data analysis are greatly enhanced. Henley and her colleagues explored data related to cancer deaths among women in the USA using hierarchical map visualization tools [66]. These visualization tools revealed regional differences in cancer incidence and mortality rates. Ben and his team conducted a study that accurately measured and interactively visualized cancer incidence among women in Missouri, stratified by age, race, cancer stage, grade and residential area from 2008 to 2012 [67]. The study employed an observational epidemiological research methodology. The spatial distribution of cases across different regions was visually presented by utilizing maps of Missouri. Finally, the incidence rates and maps were loaded into InstantAtlas software to generate interactive reports, enabling a highly intuitive and convenient presentation of research findings to relevant personnel. The study produced regional visualization representations for 34 senate districts and incorporated various forms of data presentation, such as interactive maps, charts and tables. These results visually demonstrated the differences in cancer incidence rates among different districts and provided abundant data support for subsequent analysis and research.

As a widely adopted technical approach, queue analysis plays a crucial role in exploring risk factors in populations. Its application spans various fields, including medicine, bioinformatics and social sciences, to understand deeply the characteristics and patterns of the specific subsets of the population. Zhang et al. developed CAVA, a visualization-based queue analysis platform [68]. This platform incorporates three core components: queue data, views and analysis. These components are organically connected through an innovative architecture, which provides domain experts with an interactive and exploratory analysis environment. In addition to a detailed introduction to the design of CAVA, the effectiveness of this platform was demonstrated through evaluations by medical domain experts. In addition, visualization of missing or incomplete data is a critical issue for medical research. It is mainly manifested as participant attrition or recording errors, where some individuals fail to participate in subsequent examinations. Discarding these missing data can lead to data bias and a reduction in dataset size. Moreover, such practices severely limit the effectiveness of statistical analysis and the scientific validity of research results. Visualization techniques have significant advantages in this regard by effectively analyzing and presenting patterns in missing data. Alemzadeh et al. proposed a visual analysis framework called VIVID, which specifically addresses missing values in cohort study data [69]. The concept of VIVID stemmed from in-depth discussions with epidemiologists who integrated visual elements into their current statistical analysis methods. This framework provides mechanisms for exploring missing data in depth and offers functions for data imputation and imputation effect testing, thereby enhancing the utility of data through visualization methods.

3.5 Visualization of clinical surgical scenes

Clinical treatments encompass various modalities, such as pharmacological therapy, psychotherapy and physical therapy, among others, which infrequently involve data visualization or scene visualization. Therefore, this section primarily focuses on the research related to medical imaging and scene visualization in clinical surgeries.

Medical image visualization presents complex multidimensional data in a clear and understandable manner. It also plays an indispensable role in clinical decision-making and research. However, this field faces a key challenge: creating authentic and interactive data representations to enhance doctors' experience and understanding. Against this backdrop, immersive technologies, particularly such as AR, MR and VR, have demonstrated immense application prospects. These emerging technologies have increased applications in various medical departments, where these technologies construct virtual or augmented environments thus providing users with a strong sense of presence and immersion, and this experience changes in real time based on the user's perspective and actions. In particular, AR technology overlays digital elements, enabling users to perceive additional information against the backdrop of the real world [6–8, 70–81]. VR technology constructs a fully immersive digital world where users can interact naturally with its elements [82, 83]. MR technology, a fusion of AR and VR, allows real-time and seamless interactions between users, the real world and the virtual world [82, 84–86]. Immersive technologies have been tightly integrated into surgical procedures for various purposes such as preoperative planning, intraoperative navigation and surgical training [6, 7]. Despite these significant advantages, some limitations and challenges that remain need to be addressed, such as designing highly intuitive and user-friendly interaction methods to ensure efficient and accurate interaction with the virtual environment, improving data quality to ensure the accuracy and reliability of medical images, balancing the relationship between technological development and ethical considerations to avoid potential risks and issues and further enhancing the feasibility of the technologies to reduce their costs in practical applications.

The applications of VR and AR technologies in the clinical field continuously expand, providing additional possibilities for medical services. Some major application directions are as follows. Firstly, VR technology plays a significant role in surgical simulation and training [83]. Researchers have developed various VR simulators targeting various surgical procedures, such as heart surgery, joint replacement and brain surgery [87]. These simulators offer a highly realistic surgical environment, enabling medical students and surgeons to conduct practical training. This approach enables doctors to practice surgical steps repeatedly and familiarize themselves with anatomical structures, thereby reducing operational

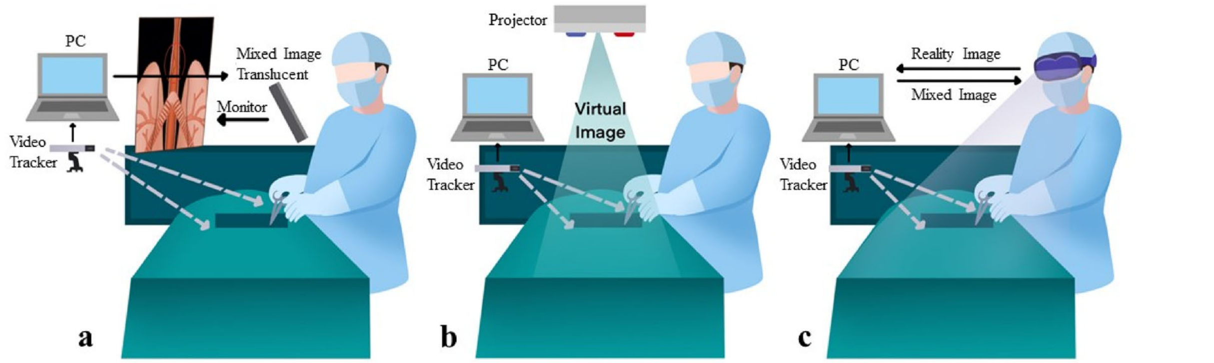

Fig. 6 Types of visualization based on AR systems. **a** Video-Based AR system, **b** Projection-Based AR system, **c** Optical-Based AR system

risks and minimizing complications during actual surgeries. Moreover, AR technology overlays virtual images in the real world during surgical procedures and assists doctors in performing highly precise and complex surgical operations, ultimately enhancing surgical success rates and safety [88]. Doctors can utilize VR devices for surgical simulation and planning by previewing surgical sites, anatomical structures and potential risks, thereby improving surgical accuracy and safety. Healthcare professionals generally employ the novel visual environments created by VR systems as preoperative training and practice tools. Conversely, AR-based clinical systems can be applied during actual surgical procedures. The technologies can be classified into clinical visualization research based on head-mounted displays, research based on optical AR systems and research based on projection-based AR systems (Fig. 6). The corresponding research contents are summarized in the following. Video-based AR systems use camera to capture real-world images and then merge them with computer-generated images. Most of the images generated by the system are displayed on the screen. Jia et al. designed an innovative AR-based computer-assisted surgical system aimed at precisely registering preoperative computed tomography (CT) models with intraoperative monocular endoscopic videos [8]. In this system, the epiglottis served as a stable anatomical marker, playing a pivotal role. The entire system encompassed several crucial steps, including the reconstruction of initial target images, the precise registration of CT models with intraoperative initial images and the dynamic tracking of target structures during the surgical procedure. During the initial map reconstruction phase, the study employed a deep learning tracking approach to effectively estimate the accurate location and morphology of the target region. In the registration process, the researchers addressed the issue of scale matching between the map reconstructed from the monocular video image and the CT model to ensure a high degree of spatial consistency between the two. During surgical execution, the registered CT model adaptively adjusts based on the real-time estimated motion state from the intraoperative video, providing doctors with an intuitive AR effect to assist in precise and safe surgical operations. This study conducted extensive qualitative experiments on clinical datasets, demonstrating the system's potential for clinical applications.

Hussain et al. developed and evaluated a video-based AR system that integrates preoperative CT data with real-time microscope videos to assist in critical steps of middle ear surgery [81]. This prospective study employed six artificially simulated human temporal bones as experimental subjects. During the experiment, researchers attached six stainless steel fiducial markers around the tympanic membrane. They acquired high-resolution CT scan data of the temporal bones. Based on these CT data, virtual endoscopic inspections of the middle ear were performed on Osirix software. Subsequently, the virtual endoscope images were precisely registered with complete tympanic membrane microscope videos using the fiducial markers. The accelerated robust features method was employed to track these movements. Additionally, a Kalman filter was utilized to identify and track a microsurgical instrument, and the three-point perspective framework was solved to extract accurately the instrument's three-dimensional (3D) position information. The results of this study indicated that the AR system achieved submillimeter accuracy without using an external tracker. Thus, it fully meets the requirements of ear surgery. This innovative system is expected to provide precise and safe auxiliary means for future middle ear surgeries and has a significant clinical application value.

Optical-based AR systems primarily place a half-lens between the real world and the eye. This approach allows the doctor to see the real world around them in a larger perspective. The optical see-through head-mounted display (OST-HMD), serves as a wearable device capable of generating AR images in real time. It provides users with an immersive visual experience. Kashiwagi et al. developed an ultrasound-guided breast tumor puncture biopsy technique leveraging OST-HMD. This technology is poised to overcome the limitations of traditional biopsy methods [80]. The study employed the Moverio BT-35E as the OST-HMD device. This technique integrates real-time projection of ultrasound images with real-time visual operation. The OST-HMD is worn, and ultrasound images are projected directly onto the display, while doctors perform the biopsy through a gap at the bottom. The results demonstrated that the technique can smoothly perform puncture biopsy operations without being constrained by patient positioning. Additionally, the flip-up design of the OST-HMD effectively enhances the clarity of image projection, which, with a transmittance of 2%, further improves the accuracy of the biopsy. This technology fully leverages the innovative advantages of AR and offers a safe and accurate new approach for biopsy operations. In recent years, the application of OST-HMD in AR technology has become increasingly widespread. However, the precise alignment between virtual scenes and physical reality remains a critical issue that needs to be addressed. In the medical field, rapid and accurate OST-HMD calibration methods are essential for achieving highly efficient AR applications. Sun et al. developed a novel OST-HMD calibration method to enhance the accuracy and reliability of AR applications in the medical domain [76]. Their study proposed a fast online calibration procedure for OST-HMD based on an optical tracking system. During this process, researchers collected two critical 3D datasets: a set of virtual points rendered in front of the observer's eyes and a corresponding set of actual points in the optical tracking space. The study successfully established a precise mapping relationship between the virtual and real spaces by solving the transformation problem between these two sets of 3D coordinates. On the basis of this calibration process, the researchers further developed an AR-based surgical navigation system and conducted experimental validation. 3D-printed skull models were used as the testing subjects for the in vivo experiments. The results revealed that the average root-mean-square error between the rendered objects and the skull models reaches millimeter-level accuracy and the entire calibration process can be completed within 30 s. This study also confirmed the feasibility of an AR-based surgical navigation system and demonstrated its clinical application potential in the medical field. Projection-based AR medical systems have shown promise in clinical surgeries. Surgeons are provided with highly intuitive and precise visual information by utilizing AR technology to reconstruct computed tomography and magnetic resonance imaging data into 3D images and overlay them in real time onto the surgical field view. This application enables surgeons to grasp the structure of the target area. It also enhances surgical precision and safety, ultimately improving patient outcomes. Tang et al. conducted a thorough analysis and summary of the literature and identified that AR-based projection techniques primarily encompass 3D reconstruction, display, registration and tracking [89].

In recent years, these techniques have gradually been applied in liver surgeries, including laparoscopic and open surgeries. Video-based AR-assisted laparoscopic resection is one of the most widely used techniques. Doctors can visualize the vascular and tumor structures within the liver in real time by employing AR technology. As a result, precise navigation for complex surgeries can be realized. However, challenges remain, such as liver deformation and registration errors during surgery. These major obstacles limit the further application of AR technology [89]. AR technology holds immense potential in hepatobiliary surgery as it promises to provide precise and safe support for surgical operations. Nevertheless, further clinical studies are necessary to evaluate comprehensively the effectiveness of AR technology in reducing postoperative morbidity and mortality and improving long-term clinical outcomes.

4 Overview

This article presents an overview of multiple critical aspects of data visualization in healthcare, encompassing the visualization of EHRs data, sensor data, omics data, public health data and clinical scenarios during surgeries. The present study explored various data visualization methods across these diverse domains to offer healthcare decision-makers and researchers a comprehensive and profound understanding that allows them to effectively leverage data visualization techniques to achieve a better quality of medical services.

EHR data visualization, a crucial aspect of healthcare, has undergone significant advancements in academic research and practical applications in recent years. This study reviewed the relevant literature to summarize several key directions for EHR data visualization, including methods based on machine learning, NLP and event sequences. These approaches have enhanced the efficiency of processing EHR data and have provided robust support for clinical decision-making and disease research. In summary, EHR visualization holds extensive application prospects and significant practical value in healthcare. We can achieve deep exploration and visual representation of EHR data and thereby provide powerful support for clinical decision-making, research and health management by integrating various technological approaches, such as machine learning, NLP and event sequence analysis [16, 112, 113].

The application of sensor data visualization in healthcare has become increasingly widespread. Its diversity provides robust support for the real-time monitoring of patient's physiological states and evaluation of rehabilitation progress [114]. Vital signs and movement data can be collected through various sensors [35, 115]. The emergence of mHealth and the continuous update and iteration of sensor technology have driven the development of telemedicine. Researchers have also adopted different visualization methods for different types of sensor data, such as analog and digital signals. Analog signal data, such as ECG waveforms, are primarily displayed as line charts, whereas digital signal data, such as heart rate and blood pressure, are presented using bar charts or pie charts. The increase in data complexity compels researchers to explore advanced and intuitive visualization techniques. In summary, the application of sensor data visualization in healthcare is deepening, and the continuous innovation of its methods and techniques provides robust support for clinical decision-making, health management and disease research.

Given the rapid development of high-throughput technologies, the field of life sciences (omics) has witnessed a deluge of biological data, accompanied by increasing complexity in data processing [5]. Against this backdrop, information visualization techniques have emerged as a crucial tool for analyzing omics and clinical data because of their intuitive and effective nature [116]. Researchers can gain deep insights into the inherent patterns of omics data and discover new clues through visual representations, such as graphs and images [117]. Various information visualization methods, including heatmaps and network graphs, are widely used in the omics field. These methods assist researchers in quickly browsing through data and help them reveal complex relationships among the data [116]. The number of software tools supporting these visualization methods increases as technology advances. Thus, researchers are provided with a complete data analysis workflow [47]. However, the application of information visualization in life sciences still faces numerous challenges despite the achievements made. The issues that require further exploration include selecting appropriate visualization methods, effectively explaining and communicating results and integrating them into existing research processes. In omics research, the development of computational and visualization methods that effectively analyze and interpret complex data based on multidisciplinary knowledge integration is crucial. These comprehensive analytical methods reveal the underlying mechanisms of biological development and providing new ideas for the healthcare field. As a core means for cell biology research and clinical applications, multi-omics analysis holds particular importance in visualization research. Nevertheless, the analysis of multi-omics datasets still faces challenges, such as data dimension expansion and interconnected complexity. In summary, the application of information visualization techniques in the omics field has great potentials. However, it is also confronted by numerous challenges. Future research should further explore the selection of visualization methods, the interpretation and communication of results and their application in multi-omics analysis.

The visualization methods of public health data exhibit a diversified trend to meet different data types and analytical needs. Common visualization techniques include statistical dot plots, two-dimensional scatter plots, choropleth maps and time-series analysis charts. These methods can intuitively display the spatial distribution, quantitative changes, variable relationships and temporal trends of public health data [118]. In particular, the visualization method based on choropleth maps effectively distinguishes data levels in different regions through visual elements, such as color and size, thereby providing decision-makers with intuitive and profound spatial data analysis tools [66]. Overall, public health data visualization methods play a crucial role in revealing the inherent patterns of data, which facilitates decision-making and helps to promote public understanding. Future research should further explore the innovation and application of visualization methods to adapt to the increasing growth and complexity of data in the public health field and to provide strong support for the sustainable development of public health undertakings.

In the clinical field, research on scene visualization in clinical surgeries has received increasing attention, with medical image visualization serving as a crucial tool that provides vital support for clinical decision-making and research [119]. However, creating realistic and interactive data representations to optimize user experience and understanding remains challenging. Recently, immersive technologies, such as AR, MR and VR, have revolutionized medical image visualization [85]. These technologies construct virtual or enhanced environments and provide users with a strong sense of immersion and presence, thereby enabling doctors to gain an intuitive and profound understanding of scenarios during surgery. AR technology allows doctors to overlay digital elements in the real world, thereby obtaining additional information. On the contrary, VR technology constructs a fully immersive digital world, enabling doctors to perform surgical simulations, planning and training. MR technology, a fusion of AR and VR, achieves seamless interaction between users, the real world and the virtual world. In clinical applications, VR and AR technologies have been widely used in surgical simulations, navigation and training. Doctors can repeatedly practice surgical steps, improve their operative skills and accuracy and reduce risks in actual surgeries through highly realistic virtual surgical environments. Additionally, these technologies can assist doctors in performing high-precision and complex surgical operations, thereby enhancing surgical success rates and safeness. Despite this promising application prospects of immersive technologies in medical image visualization, limitations and challenges still exist. For instance, highly intuitive and user-friendly interaction methods must be designed, data quality should be improved to ensure the accuracy of medical images, the relationship between technological development and ethical considerations must be balanced, and the cost of applications should be reduced. In summary, immersive technologies provide powerful support for scene visualization research in clinical surgeries. However, further exploration and improvement are still needed. Future research should address existing challenges, optimize technological performance and user experience and promote the widespread application of medical image visualization in clinical practice.

4.1 Findings

In summary, our main findings are as follows:

1. Data visualization techniques significantly improve healthcare professionals' understanding of patient data and medical conditions [119]. Through intuitive charts, images or animations, physicians can quickly identify patterns and trends in the data and then to make diagnostic and treatment decisions [120].
2. Traditional data analysis methods are mostly reliant on using historical data. Nowadays, visualization technologies can display changes in real time, such that allows to make clinical decisions more rapid and accurate [121]. In addition, through the integration of artificial intelligence technology, data visualization is no longer a static display of charts and graphs, but also real-time prediction and pattern recognition, providing more advanced support for medical decision-making [2, 15].
3. In the field of healthcare, data often originates from multiple different channels and formats, such as EHR, medical images and laboratory test results. Data visualization techniques can effectively integrate these diverse and heterogeneous data and assisting healthcare workers to better understand the health status of patients [2].
4. Data visualization can also help patients to better understand their health conditions such that enhance patients' understanding of their own health status and eventually improve the effectiveness of treatment [102, 115].
5. There has been great research focus on using data visualization techniques for medical research and education purposes. Medical researchers can use visualization technology to analyze large-scale medical data and to explore disease mechanisms, risk factors and treatment effects. With the educators, these techniques can be used to better demonstrate and understand the complex medical concepts/surgical operations [71, 82].

4.2 Future directions

With the growing trend of diverse data types, e.g., different imaging modalities, text report, omics data, how to efficiently integrate and visualize heterogeneous data from multiple sources is one of major challenges. However, current methods, including early fusion, intermediate fusion, late fusion, etc., still have difficulties in identifying data redundancy and semantic gaps across different data sources. In addition, the problem of missing or incomplete data is limiting the capabilities in interpreting data analysis results. This issue may be minimized by combining statistical methods and visual elements to enhance data utilization. With the recent development of generative artificial intelligence techniques, the missing data can also be augmented with generative AI for visualization.

5 Conclusion

This article presents an overview of the applications and advancements of data visualization across various fields in healthcare. These visualization techniques have significantly supported medical decision-making, research and clinical practice. However, they still face several challenges, including increasing data complexity, evolving demands for interactive approaches, advancements in data processing technology, ethical considerations and relatively high technological costs. Future research should address these challenges and promote the widespread application of visualization techniques in the medical field. As a result, medical standards and service quality can be enhanced further. In summary, the application of visualization techniques in the medical field holds vast potential and possesses significant theoretical and practical value. The continuous optimization and improvement of these techniques are expected to contribute greatly to the development of the medical industry and the well-being of human health.

Author contribution XT, LB and FY contributed to concept and design and drafting of the manuscript. XT, XS and WL were involved in literature selection. FY and LB contributed to critical revision of the manuscript for important intellectual content, administrative, technical or material support and supervision.

Data availability No datasets were generated or analyzed during the current study.

Declarations

Conflict of interest The authors declare no competing interests.

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