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Review

A Review of Perioperative Databases for Anesthesiology in China: Current Status, Applications, and Challenges

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ABSTRACT

In recent years, advancements in medical technology, artificial intelligence (AI), and the advent of the big data era has led to the emergence of perioperative databases as crucial tools for enhancing clinical decision-making, optimizing perioperative management, and advancing clinical research. This review provides a systematic evaluation of the evolution of perioperative databases from a global perspective, with a particular emphasis on the current state of the field in China. By synthesizing extant literature, the study assesses technological advancements and clinical utility within anesthesia management while conducting a comparative analysis of domestic and international progress. The review further identifies problems and challenges in database construction, provides suggestions for future development directions, and serves as a reference for anesthesia departments and healthcare institutions to establish robust perioperative data platforms.

Keywords—*Perioperative period, Database, Anesthetic management, Artificial intelligence, Personalized medicine.*

INTRODUCTION

Background and Significance

In recent years, advances in medical technology and improvements in medical conditions have driven a marked increase in surgical volume—particularly for complex high-risk procedures. Concurrently, a growing patient population and greater case complexity have led to an explosion of clinical data, while limited medical resources make precise decision-making increasingly challenging. How to leverage these data to optimize perioperative management, improve diagnostic and treatment efficiency, and reduce surgical risk has thus become a major research focus. Against this backdrop, perioperative databases have arisen to provide vital data support for precision medicine and to open new avenues for clinical practice and scientific research. Perioperative database refers to a clinical information system dedicated to recording, managing, and analyzing patients' perioperative data. Compared to traditional Electronic Medical Records (EMR) or Hospital Information Systems (HIS), perioperative databases offer greater specificity by integrating comprehensive patient data—from preoperative assessment and intraoperative monitoring to postoperative recovery—within a standardized, systematic, and structured framework. This enhances both data availability and interoperability, facilitating retrospective clinical research, clinical decision support, and educational or research applications.[1]

The construction of perioperative databases originated from the supplementation and optimization of traditional surgical record-keeping methods, which began from the mid-to-late 20th century to the early 2000s. In 1988, the Mayo Clinic in the United States established the Performance Improvement Database, an electronic anesthesia quality assurance system used to track perioperative cardiovascular adverse events, marking the beginning of systematic clinical data collection.[2] In 1999, Peking Union Medical College of China developed the Perioperative Patient Information System (PPIS), which is a representative of early automated information processing, with automatic anesthesia record-keeping, data query, and statistical analysis.[3] With the gradual maturation of data storage technologies and information systems, especially in high-risk surgical fields, some hospitals began to explore the establishment of perioperative databases. These databases not only record information, such as the patient's underlying disease, type of surgery, use of anesthetics, and postoperative complications but also facilitated surgical risk assessment and prediction of postoperative recovery through data integration. For example, in 2016, Singapore General Hospital established the Perioperative and Anesthesia Subject Area Registry (PASAR) database, which integrates full-cycle data from the preoperative, intraoperative, to postoperative stages. Currently covering over 150,000 surgeries, it has become a model of automated data collection.[4] Nevertheless, databases during this period still faced problems, such as inconsistent data standardization and poor interoperability, which limited the broader application of databases and the efficiency of data integration. The rapid development of big data technology in recent years, especially the introduction of artificial intelligence (AI) and machine learning (ML), has enabled these databases to go beyond mere data storage, allowing for intelligent analysis of large volumes of complex data to support personalized medicine and precision anesthesia management. For example, in the design of specialty data platforms for anesthesiology and perioperative medicine, natural language processing (NPL) technologies have been integrated to further process data, thereby improving data usability and accuracy.[5]

Therefore, this review evaluates the development of perioperative databases from a global perspective, with a specific focus on their status in China and their applications in anesthesiology. By providing a comparative analysis of the construction, clinical implementation, and existing challenges of these databases, this review analyzes progress in recent research and explores future directions—thereby providing a valuable reference for researchers and clinical practitioners in related fields.

Methodology

For this review, a systematic literature search was conducted across major databases, including PubMed, Web of Science, China National Knowledge Infrastructure (CNKI), Wanfang Data, and VIP Chinese Science and Technology Periodicals Full-Text Database. The search strategy utilized key terms, such as "perioperative database", "anesthesia", "clinical database", "artificial intelligence", and "perioperative management." The review incorporated domestic and international literature published between 2000 and 2025, specifically focusing on the studies related to the construction, application, or challenges of perioperative databases. Conference abstracts, duplicate publications, and irrelevant articles were excluded to ensure quality and pertinence. While the review spans the period from 2000 to 2025, it places particular emphasis on advancements over the last decade (2015–2025) while also including landmark studies from 2000 to 2015 to provide a comprehensive technical background.

CURRENT LANDSCAPE OF PERIOPERATIVE DATABASES

Data Standardization

Data standardization refers to the process of converting data from various sources and formats into a unified standard to improve data consistency and comparability. In the construction of perioperative databases, because of the fact that a large volume of data originates from different hospital systems (as shown in Figure 1), issues such as data fragmentation and poor data quality arise, making it necessary to standardize the data during the database building process. Data standardization allows for the integration of multi-source data, such as preoperative assessments, intraoperative monitoring, and postoperative follow-up, thereby enhancing data quality and improving the interoperability of the database. At present, database information unity and the standardization of formats should be developed with reference to relevant domestic and international standards and guidelines, as well as disease classification systems, in order to formulate corresponding data set standards.[6] For example, a perioperative anesthesia specialty database was established based on a Greenplum big data solution, in combination with data standards from the Clinical Data Interchange Standards Consortium (CDISC). This enabled integration, governance, and quality control of patient data and led to the development of a big data application platform, which supports both research and clinical decision-making.[7]

At present, the following technologies are primarily used in data standardization:

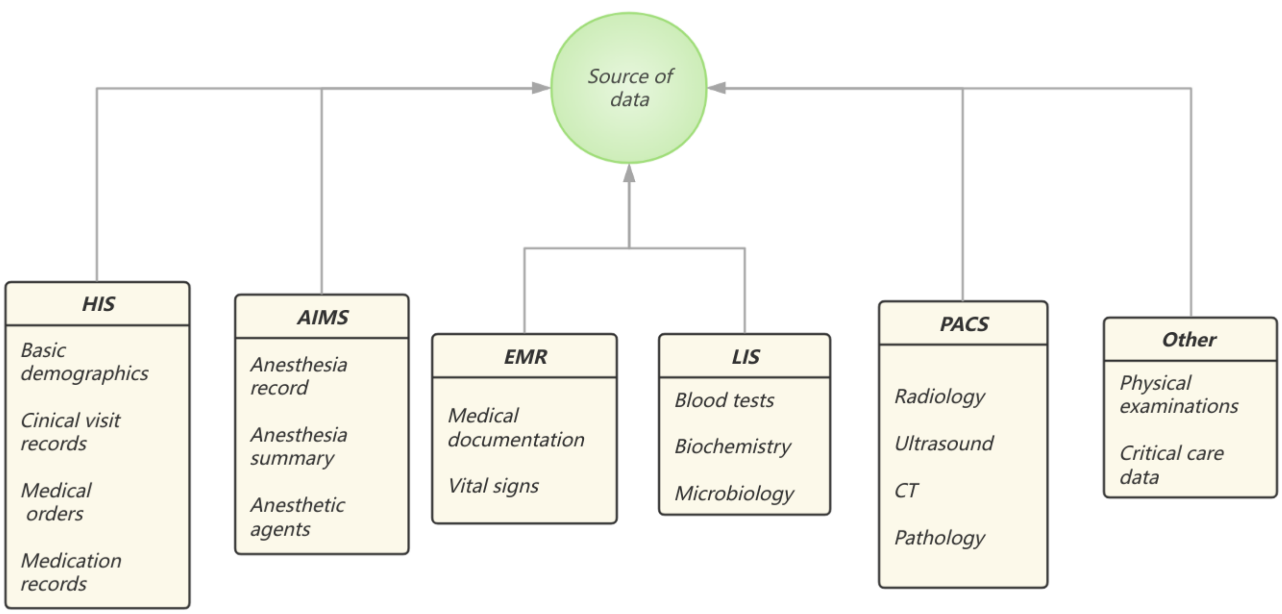

FIGURE 1. Sources of data in perioperative databases. (HIS: Hospital Information System, EMR: electronic medical record, PACS: Picture Archiving and Communication System, AIMS: Anesthesia Information Management System, and LIS: Laboratory Information System.)

Application of Natural Language Processing Technology

Natural Language Processing is an AI technology that enables computers to understand, analyze, and generate natural language text. In the construction of perioperative databases, NLP technology can automatically extract key information such as patient medical history, intraoperative records, and laboratory reports, and is widely used for the collection and standardization of unstructured data.[8] For example, semantic analysis and structured processing of clinical texts using NLP models can convert free text into usable data formats. This method not only improves data usability but also addresses the problem of inconsistent data standards.[9] Based on structured electronic medical records, Longhua Hospital in Shanghai established a sub-center of a psoriasis specialty database. By using templated input and NLP technology, unstructured electronic medical records were converted into structured records, thereby improving the standardization and usability of the specialty database and enhancing the efficiency of clinical research work.[10] This successful implementation provides a valuable technical reference for the construction of anesthesia-oriented perioperative databases.

Extract, Transform, and Load (ETL) Technology

Extract, transform, and load technology refers to the process of extracting, transforming, and loading data. It can extract information from heterogeneous data sources and transform it into a standard data format before storing it in the database to support efficient querying and analysis. For example, the Multicenter Intensive Care Unit Database in the Netherlands integrates data from 25 hospitals through ETL and data pipeline processes, covering over 200 million clinical data points. These data include detailed information on the Corona Virus Disease 2019 (COVID-19) patients, such as daily vital signs and medication usage, which provide important data support for critical care medicine research.[11]

Multicenter Collaboration and Data Sharing

Perioperative databases involve multidimensional data, with medical institutions differing in patient groups, treatment procedures, and other factors. Establishing mechanisms for multicenter collaboration and data sharing can support in-depth research on complex conditions, optimize individualized treatment plans, and enhance the breadth and representativeness of studies. The multicenter collaboration among 18 hospitals, including the Chinese PLA General Hospital, achieved the integration and sharing of perioperative medical data through data ferrying technology based on the perioperative data standards.[12] The Shanghai Shenkang Hospital Development Center, in collaboration with 10 municipal hospitals, realized interoperability between hospital information systems and data platforms through big data technologies. This database utilizes AI to conduct deep governance of clinical data, and achieves cross-regional data sharing through the Medical Union Project, thereby improving the capacity for medical research, epidemic prevention, and control.[13] The Electronic Databases Alliance for Perioperative Outcomes Research in China (EPOCH), led by Nanfang Hospital of Southern Medical University, established a shared mechanism for multicenter perioperative databases, providing data support for high-quality research on perioperative outcomes. This initiative aimed to advance the discipline of anesthesiology and perioperative medicine and improve patient outcomes during the perioperative period.

Construction of Perioperative Databases

In China, although medical informatization started relatively late and the population base is large, perioperative databases have developed rapidly in recent years. Based on a self-developed clinical research database, the department of anesthesiology at the Affiliated Hospital of Southwest Medical University conducted a retrospective cohort study of more than 13,000 surgical patients, revealing the association between preoperative cerebrovascular disease and perioperative neurocognitive disorders, and laying foundation for the development of risk prediction models.[14] The construction of a perioperative database led by Professor Ke-Xuan Liu at Nanfang Hospital has improved medical management efficiency, supported large-scale clinical research, and helped to identify surgical risk factors and develop personalized anesthesia plans. Based on this database, it was found that preoperative cardiac biomarker N-terminal pro-B-type natriuretic peptide (NT-proBNP)[15], and preoperative echocardiographic indicator Left Ventricular Ejection Fraction (LVEF)[16] were independently associated with increased risk of adverse postoperative outcomes. These findings provide new ideas and methods for the precise prediction and management of perioperative organ injury, promotion of postoperative recovery, and improvement of long-term outcomes. Similarly, the department of anesthesiology at West China Hospital, Sichuan University, leveraged its perioperative database established in 2018 to optimize clinical outcomes. By evaluating six distinct ML models, researchers identified the most effective algorithm for predicting postoperative pulmonary complications (PPCs). To enhance model interpretability, the research team employed the SHapley Additive explanations (SHAP) method to quantify the significance of specific clinical features, ultimately developing a risk assessment tool for clinical practice.[17] These efforts are of paramount importance for informing clinical decision-making and improving postoperative patient management.

In foreign countries, owing to earlier medical informatization and more mature technological development, the establishment of perioperative databases is relatively complete. The Lille University Hospital in France has developed an anesthesia data warehouse that encompasses all events within the operating room, diagnoses, and medical procedures during hospitalization as well as biological test results, transfusions, and mortality data. This data warehouse has supported 120 retrospective studies and promoted multicenter research through the use of federated learning methods.[18] The Tourette Association of America established a comprehensive international Deep Brain Stimulation (DBS) surgery database to collect detailed data on patients before, during, and after surgery, which facilitates collaboration between clinicians and researchers and provides better treatment options for patients.[19] Vanderbilt University Medical Center in the United States developed a system called Nimbly based on its perioperative database. This system enables anesthesiologists to clearly query specific types of surgeries and rapidly obtain an annotated summary of key anesthetic details from recent procedures. Cross-validation has shown that Nimbly significantly improves case preparation efficiency for anesthesia residents.[20] The Enhanced Recovery after Surgery Interactive Audit System (EIAS) is an international perioperative care database developed by the Enhanced Recovery After Surgery (ERAS)® Society, aiming to optimize surgical patient recovery pathways (ERAS Guidelines) through standardized data collection and audit.[21] It covers healthcare institutions across Europe and includes full-cycle data for the 30-day perioperative period, with more than 300 variables, including patient characteristics, surgical details, and complications.

An analysis of the current state of perioperative database construction and application in China and abroad reveals notable differences in terms of development foundations, research priorities, and other related aspects, along with some shared characteristics, as shown in Table 1.

As shown in Table 1, substantial differences exist between perioperative database development in China and Western countries. These differences largely arise from distinct driving forces: in China, perioperative databases are primarily driven by the need to balance safety and efficiency under high surgical volumes, whereas European systems emphasize public accountability and cost optimization, and North American systems are largely driven by market competition, profit incentives, and innovation.[22] Notably, Western countries maintain a competitive advantage in healthcare innovation. Their mature clinical documentation systems, well-established research and development (R&D) mechanisms, and international talent cultivation models have collectively contributed to the maturity of Western perioperative databases,[22] which represent important development directions for perioperative databases in China.

PERSPCETIVES FOR FUTURE DEVELOPMENT

In China, although the construction of perioperative databases has made significant progress, significant difficulties and challenges persist.

The development of medical informatization remains uneven across regions, characterized by a lack of unified industry standards for underlying data and poor interoperability.[23] Furthermore, there are inherent limits to database unification; differences in clinical practice patterns, patient populations, and medication standards across institutions can adversely affect data comparability and the validity of multicenter perioperative database constructions. Additionally, the data processing stage involves a massive volume of information and low efficiency, while issues, such as low construction rates, limited disease coverage, and narrow geographical reach, remain to be resolved.

In terms of anesthesia management, current research focuses on whether vast data from electronic medical records, laboratory, and imaging systems, and perioperative anesthesia systems can be effectively leveraged to develop specialized anesthesia databases that are clinically applicable and replicable. Such efforts are critical to standardizing data collection, promoting single-disease or multicenter clinical research[24], and optimizing individualized anesthesia protocols.

Addressing these issues, this review discusses the future development directions of perioperative database construction and application in China from three aspects.

Enhancing Data Integration and Multidisciplinary Cross-Center Collaboration

Perioperative management needs to cover various diseases (such as thoracic diseases, retroperitoneal tumors, and cardiovascular and cerebrovascular diseases), which differ significantly in terms of complication types, risk factors, and interventions. At present, most perioperative databases focus on a single disease, but with the improvement of living standards and the increasing severity of health problems, many patients often present with multi-system comorbidities.[25] A single database can no longer meet the needs of treating and studying complex cases.[25] Therefore, it is imperative to strengthen the standardization and integration of multi-source heterogeneous data, and to establish more comprehensive cross-disciplinary and cross-center collaboration mechanisms. This will enhance data interoperability and promote the development of

TABLE 1. Comparative analysis of perioperative databases in China and abroad.

Aspect	Domestic Databases	International Databases
Data Architecture	Predominantly single-center, rapidly evolving toward regional integration.	Established multicenter global networks with mature data federations.
Data Granularity and Depth	Focused on perioperative snapshots, including patient characteristics, comorbidities, and high-resolution intraoperative physiological waveforms.	Encompasses longitudinal, full-process data, including granular preoperative baselines and extended long-term postoperative follow-up.
Data Standardization	Data standards under development, heterogeneity exists across institutions.	Relatively mature data standards and harmonized data schemas.
Research Focus	Predictive modeling for acute complications (e.g., hypotension and PPCs).	Population health management, surgical outcomes, and cost-effectiveness analysis.
Informatics Maturity	High integration with domestic AIMS, EMR-based NLP extraction is a current trend.	Mature integration across disparate HIS/LIS platforms with automated registry reporting.
AI and Advanced Analytics	Increasing application of machine learning for specific clinical problems, often within single-center datasets.	Broad application of AI and advanced analytics, including externally validated multicenter models.

Note: PPCs: postoperative pulmonary complications, AIMS: Anesthesia Information Management System, EMR: electronic medical records, NLP: Natural Language Processing, HIS: hospital information systems, and LIS: laboratory information system.

multidisciplinary perioperative databases from the current single-disease model.

At the same time, although some multicenter collaborative databases have already been established, because of uneven regional development, the reported databases are mainly concentrated in economically developed coastal provinces and cities[1], with limited coverage. This regional concentration reflects underlying institutional and economic characteristics of the Chinese healthcare system. Coastal regions typically host a higher proportion of manufacturing and high-value industries, which generate stronger local fiscal capacity and enable greater investment in hospital information infrastructure, digital health platforms, and data-driven research initiatives.[26] In addition, large tertiary hospitals in these regions often serve as regional referral centers with higher surgical volumes and more mature information systems, making them early adopters of perioperative database construction.[27] Therefore, it is also essential to establish regional or national perioperative databases, develop the underlying architecture of distributed data platforms, and support complex cross-system queries and automated data extraction to further promote multicenter collaboration and data sharing.

Application of Artificial Intelligence and Its Algorithms

Perioperative management involves medical decision-making and risk control throughout the entire surgical process—preoperative, intraoperative, and postoperative. There are problems such as data fragmentation, decision-making relying on experience, and lagging in the prediction of complications in the traditional mode. In recent years, with the rapid development of ML and deep learning, algorithms such as Random Forest, K-Nearest Neighbors (KNN), Convolutional Neural Networks (CNN), and Long Short-Term Memory (LSTM) networks have demonstrated superior performance in handling complex data and can be applied to the future construction and application of perioperative databases. During the construction of perioperative databases, because of the fact that in modern medicine, patient data come from various departments or institutions, discrepancies often exist in data formats and other aspects. Consequently, it is necessary to perform a series of processing steps on this data to enhance its integrability and shareability. In the future, AI algorithms can be introduced into these processing steps to improve the efficiency of data handling for database entry and reduce the difficulty of database construction. This review summarizes potential AI algorithms and their functions that can be introduced during the data governance stage, as illustrated in Figure 2, to provide references for the construction of perioperative databases. For example, Wenwen et al. applied AI techniques such as NLP, Knowledge Graphs, and ML to achieve structuring, standardization, and normalization of various types of medical text data for the construction of disease-specific databases.[28] In addition, algorithms can also be used to analyze data from perioperative databases for purposes such as intraoperative risk prediction, real-time anesthesia depth monitoring, and postoperative complication forecasting, thereby maximizing the potential and broadening the scope of perioperative database applications.

Personalized Medicine and Precision Treatment

Perioperative databases play a critical role in personalized medicine and precision treatment. These databases collect extensive clinical data on patients during specific periods before and after surgery. By integrating the data within perioperative databases, multidisciplinary collaboration can be better facilitated, enabling the development of more personalized treatment plans.[29] For example, researchers utilized the Perioperative Data Warehouse of the department of anesthesiology and perioperative medicine at the University of California, Los Angeles, CA, to extract perioperative data, including demographic characteristics, laboratory test results, medication information, and care team variables. Based on this perioperative database, ML models were developed to predict 30-day postoperative readmissions via the emergency department. This study illustrates how perioperative databases can support early prediction of postoperative complications or adverse outcomes and facilitate timely clinical decision-making in perioperative care.[30] As illustrated in Figure 3, the future applications of perioperative databases in the domain of personalized medicine throughout the various stages of perioperative period are summarized and presented.

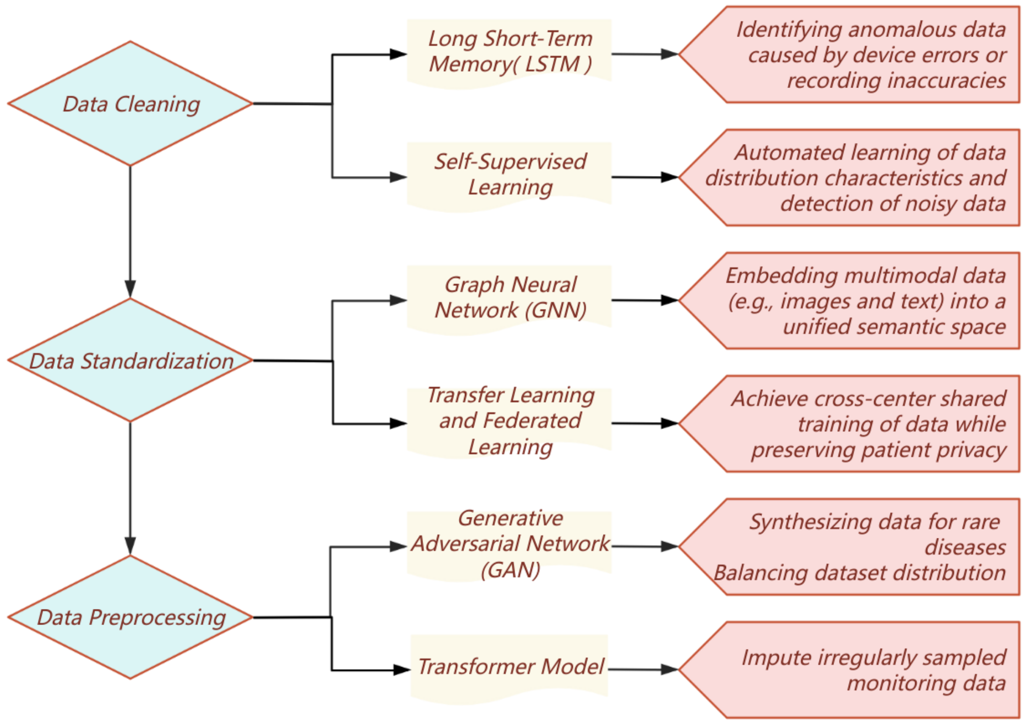

FIGURE 2. Potential AI algorithms and their roles in the data governance stage.

CONCLUSION

Perioperative databases play a pivotal role in bridging clinical practice with scientific research, driving anesthesiology toward precision and intelligence. By integrating comprehensive datasets—encompassing preoperative evaluations, intraoperative vitals, anesthesia records, and postoperative outcomes—these platforms enable the formulation of personalized treatment strategies and the predictive modeling of adverse events, such as hypotension and delirium. Although advancements in AI and big data have enhanced data integration capabilities, significant hurdles persist in interoperability and multicenter collaboration. Future progress must rely on robust policy support, reinforced technical infrastructure, and the establishment of cross-institutional data-sharing mechanisms. Such initiatives will facilitate the transition of perioperative databases from mere data accumulation to powerful real-time clinical decision support, ultimately advancing medical research and ensuring efficient and safe perioperative management.

To further advance the construction and development of perioperative databases, we propose the following strategic recommendations:

1. Prioritize NLP and automated templating to convert unstructured anesthesia notes and EMRs into structured data, thereby ensuring clinical data integrity and depth.

2. The establishment of multicenter specialty registration systems should be prioritized, particularly for high-risk surgical populations and complex procedures, to mitigate single-center biases and enhance the validity of clinical research.

3. Accelerate database deployment in small and medium-sized hospitals to reduce geographical data disparity.

4. Perioperative databases should be seamlessly integrated into the existing hospital information systems (HIS, Laboratory Information System [LIS], Picture Archiving and Communication System [PACS], and Anesthesia Information Management System [AIMS]). This integration will streamline data extraction for retrospective studies

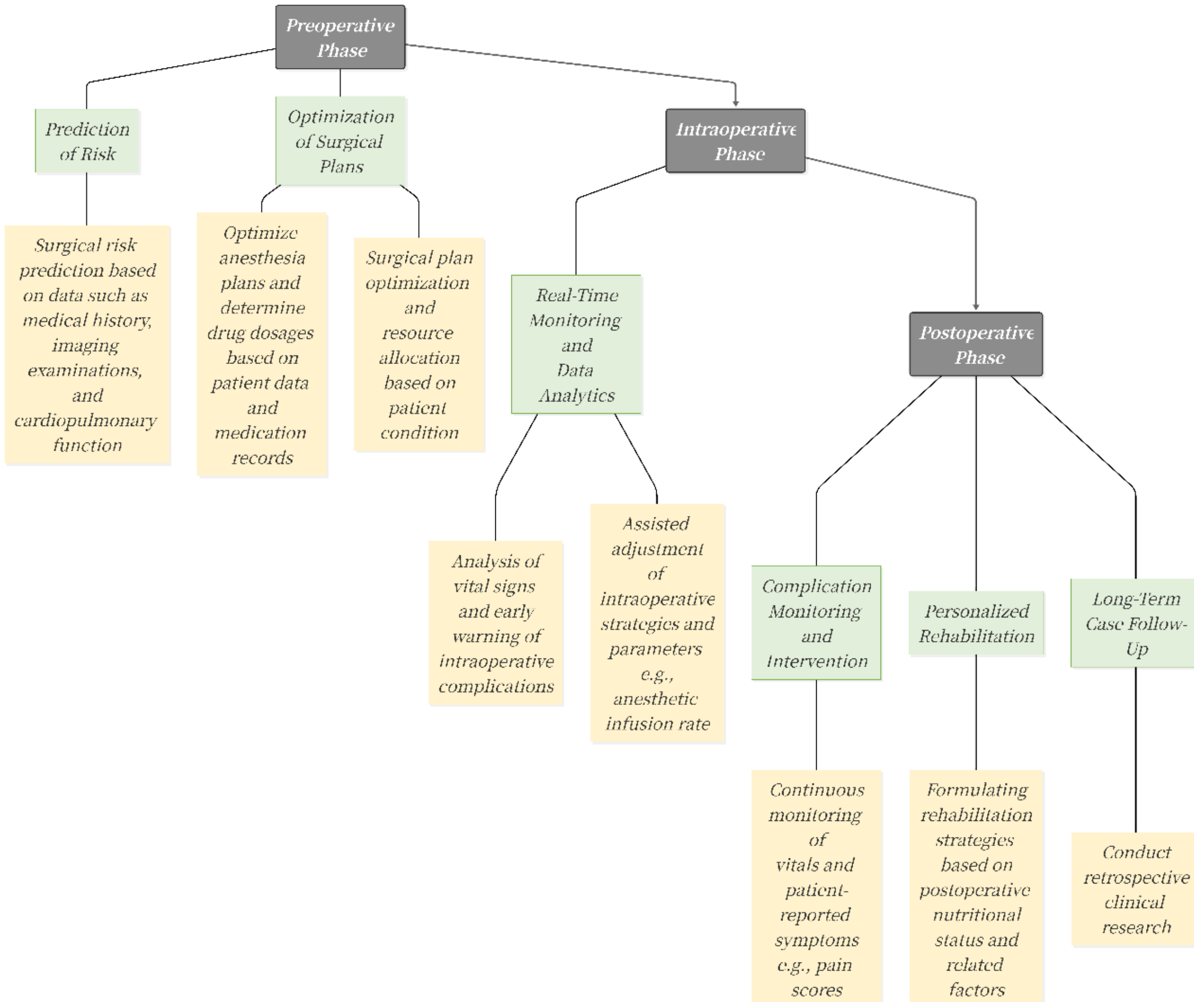

FIGURE 3. Personalized medicine applications enabled by perioperative databases.

and facilitate the development of real-time clinical decision support systems (CDSS), ultimately enhancing intraoperative safety and personalized care.

5. To ensure multi-system data collectability and scalable multicenter expansion during perioperative database construction, internationally recognized healthcare data exchange standards should be adopted, such as Health Level Seven (HL7) and Fast Healthcare Interoperability Resources (FHIR).

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CONSENT FOR PUBLICATION

Not applicable. This study is a literature review and does not involve human participants.

AVAILABILITY OF DATA AND MATERIALS

Not applicable. This review article is a narrative review and does not involve newly generated datasets.

ETHICS APPROVAL AND CONSENT TO PARTICIPATE

Not applicable. This study is a literature review and does not involve human participants or animal experiments.

AUTHOR CONTRIBUTIONS

Conceptualization, Q.M.; Methodology, W.C.Q.; Writing–Original Draft Preparation, W.C.Q.; Writing–Review & Editing, X.X.Z., J.Q.G., Z.Z.; Supervision, Q.M.

CONFLICT OF INTEREST

The authors declared that they had no competing interests related to this work.

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DATA AVAILABILITY STATEMENT

Not applicable.

FURTHER DISCLOSURE

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