

Review

Open Access



Data quality for safer and more personalized perioperative care: a scoping review

Massimiliano Greco^{1,2}, Ilesa Bose¹ , Brenda Lupo Pasinetti^{1,2}, Maurizio Cecconi^{1,2}

¹Department of Biomedical Sciences, Humanitas University, Milan 20072, Italy.

²Department of Anesthesia and Intensive Care, IRCCS Humanitas Research Hospital, Milan 20089, Italy.

Correspondence to: Ilesa Bose, Department of Biomedical Sciences, Humanitas University, Via Rita Levi Montalcini, Milan 20072, Italy. E-mail: ilesa.bose@hunimed.eu

How to cite this article: Greco M, Bose I, Pasinetti BL, Cecconi M. Data quality for safer and more personalized perioperative care: a scoping review. *Art Int Surg*. 2025;5:361-76. <https://dx.doi.org/10.20517/ais.2024.100>

Received: 25 Nov 2024 **First Decision:** 30 May 2025 **Revised:** 22 Jul 2025 **Accepted:** 25 Jul 2025 **Published:** 30 Jul 2025

Academic Editors: Andrew Gumbs, Eyad Elyan **Copy Editor:** Pei-Yun Wang **Production Editor:** Pei-Yun Wang

Abstract

Background: The exponential growth of perioperative data generated by monitors, electronic health records (EHRs), and wearable devices (WD) represents a significant promise for improving risk assessment, preventing complications, and personalizing perioperative care. Perioperative care produces a wide range of data types from diverse sources (e.g., intraoperative monitors, EHRs, and WD) that can be analyzed using machine learning (ML) techniques. The use of data-driven techniques to big data from perioperative medicine is being extended to different settings of perioperative care, including risk prediction, intraoperative monitoring, complication reduction, and decision support. However, the quality of these data often remains uncertain, potentially limiting the effectiveness of even the most advanced models.

Objective: This scoping review maps the current literature on perioperative data quality. It explores common quality challenges (such as missing, inaccurate, or non-standardized data) and highlights tools, frameworks, and methodologies, from harmonization standards to ML-based imputation techniques. We address the challenges of ensuring adequate data collection, data accuracy, and consistency. We emphasize the importance of data standardization and harmonization through common models to facilitate interaction and integration among different hospitals, systems, and countries. Such efforts aim to enhance external validation and bridge the translational gap from bench to bedside.

Design: We included English-language publications that addressed perioperative data quality issues. We searched PubMed and reviewed the reference lists of relevant articles. Two independent reviewers selected studies and



© The Author(s) 2025. **Open Access** This article is licensed under a Creative Commons Attribution 4.0 International License (<https://creativecommons.org/licenses/by/4.0/>), which permits unrestricted use, sharing, adaptation, distribution and reproduction in any medium or format, for any purpose, even commercially, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons license, and indicate if changes were made.



extracted data. Our analysis focused on four key topics: data accuracy, handling of missing data, standardization, and harmonization.

Results: Of the 342 publications, many highlight that perioperative data derive from multiple sources, including intraoperative monitors, ICU systems, EHRs, registries, and WD. Missing values, artifacts, and uneven documentation were common challenges. Studies reported that using advanced filtering and imputation algorithms, standard vocabularies (like SNOMED CT and LOINC), and common data models (CDMs, such as OMOP) improved data sharing and use. Initiatives like the Multicenter Perioperative Outcomes Group (MPOG) demonstrated how harmonized datasets could drive multi-institutional quality improvement and research.

Conclusions: This review focuses on perioperative data quality; we translate technical methods into practical strategies for data-driven perioperative care. It highlights the strong link between data quality and improved perioperative care. Achieving the diffusion of reliable and standardized data calls for strategic efforts on regulatory alignment, staff training, and the development of large collaborative networks. As perioperative medicine evolves, high-quality data will serve as the foundation for reliable predictive modeling, safer anesthesia management, and more patient-centered approaches.

Keywords: Data quality, perioperative care, machine learning, data standardization, data harmonization, predictive modeling, interoperability

INTRODUCTION

In recent years, a large volume of perioperative data has become available from sources such as intraoperative monitors, anesthesia records, and bedside devices. Researchers and clinicians can leverage this volume of data to advance personalized and patient-centered perioperative care. There are two main factors driving this revolution. On one side, the rapid integration of data science into perioperative medicine is transforming clinical practice, enabling doctors to use these data for research and quality improvement purposes.

On the other side, there is an increasing prevalence of elderly and frail patients undergoing surgery, and this in turn increases the need for advanced monitoring. Advanced monitoring systems generate high-resolution data^[1], offering further potential for analysis and decision making.

However, leveraging these data is neither straightforward nor without risks. The effective use of data depends mainly on the reliability of data sources and the quality and integrity of the collected data, as data are often riddled with inaccuracies, missing values, and incompatible formats^[2,3]. Without high-quality data collection, even the most advanced analytic model will fail.

This scoping review maps out the current landscape of perioperative data quality initiatives, highlighting challenges, exploring current strategies, and identifying opportunities for future growth.

METHODS

Study protocol

A study protocol was developed in accordance with the Joanna Briggs Institute (JBI) methodology for scoping reviews and the PRISMA-ScR reporting guidelines. The protocol is available upon reasonable request. The completed PRISMA-ScR checklist is available as [Supplementary Materials](#).

Eligibility criteria

We included peer-reviewed articles, reports, and frameworks addressing perioperative data quality. Eligible studies addressed one or more data quality dimensions such as accuracy, completeness, standardization, harmonization, or interoperability. We did not restrict the search to any specific perioperative setting, data type, or phase of clinical care.

Information sources

The literature search was conducted on PubMed, using relevant keywords (e.g., “perioperative”, “data quality”, “missing data”, “EHR”, “standardization”, “interoperability”).

Search strategy

The search covered literature published between January 1, 2000, and December 31, 2024. Additional filters restricted the search to English-language articles and excluded preprints.

The following query was used to search for relevant articles:

(“big data”[Title] OR dataset[Title] OR “remote monitoring”[Title] OR wearable[Title] OR “data standardization”[Title/Abstract] OR “missing data”[Title/Abstract] OR “data imputation”[Title] OR “data harmonization”[Title/Abstract] OR FHIR[Title/abstract] OR EHR[Title/Abstract] OR Common Data Models[Title/Abstract]) AND (anesthesiology[Title] OR preoperative[Title] OR perioperative[Title] OR postoperative[Title]) AND (excludepreprints[Filter]) AND (2000/1/1:2024/12/24[pdat]) AND (english[Filter]).

In addition to the primary search conducted, the references from the initial studies were examined to include relevant articles. This cross-referencing approach helped capture studies that were not retrieved through the database search. Articles identified by the authors as relevant were included.

Selection and charting process

Two reviewers independently screened all retrieved references. A third reviewer resolved conflicts. We charted relevant information, including data sources, identified quality issues, and proposed interventions. The selection of articles was based on the following criteria:

Inclusion criteria:

- English-language publications from January 2000 to December 2024
- Methodological papers, observational studies, registry reports, and narrative reviews
- Studies conducted in any perioperative phase (preoperative, intraoperative, postoperative)
- Focus on perioperative data quality, missing data, standardization, or harmonization
- Articles addressing data integration, interoperability, or common data models (CDMs) in perioperative care

Exclusion criteria:

- Non-English language publications
- Studies not focused on perioperative settings
- Articles that did not address any aspect of data quality
- Preprints and non-peer-reviewed publications
- Studies in which data quality was neither a primary nor a secondary outcome

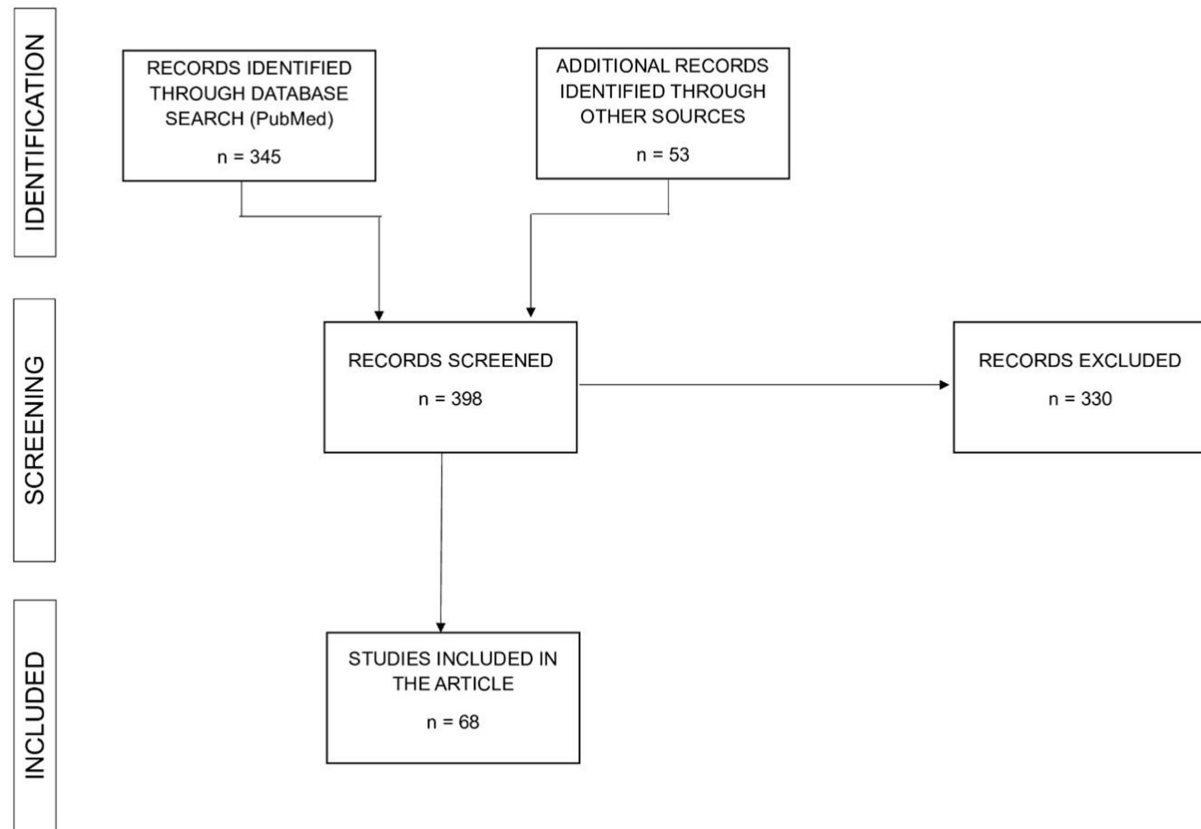


Figure 1. Study flow chart.

The study flow chart is reported in [Figure 1](#).

Synthesis of results

We organized findings into thematic clusters: (1) perioperative data sources and inherent challenges, including missing data and imputation; (2) standardization and interoperability frameworks; and (3) impact of data quality on patient safety and outcomes.

RESULTS

After excluding 345 articles from the database search, we included 15 articles encompassing observational studies, methodological papers, registry reports, conference papers, and narrative reviews. An additional 53 papers were identified from sources beyond the database search. In total, we included 68 papers, mostly published after 2010.

Sources of data in perioperative medicine

The operating room is among the most intensively monitored environments in the hospital. Each operating room typically includes ECG monitoring, pulse oximetry, cutaneous or core temperature measurement, invasive or non-invasive blood pressure monitoring, respiratory rate, and capnography (EtCO₂).

Monitoring the depth of anesthesia helps to avoid excessive use of hypnotics by relying on continuous electroencephalogram (EEG) analysis. Predictive models have also been used to avoid hypotension, alerting physicians several minutes before it becomes apparent. These monitoring tools enable anesthesiologists to

detect and manage complications at an early stage. [Figure 2](#) reports distinct types of monitoring systems, grouped by clinical setting. Continuous postoperative vital parameter monitoring can also be applied in standard wards. This is useful for detecting and preventing clinical deterioration in patients who are at risk for complications, even if they do not require intensive unit-level monitoring^[4-7]. In contrast, when surgical patients experience complications or need the highest level of assistance, they are admitted to the ICU. In the ICU, advanced monitoring techniques are used besides continuous monitoring, including calibrated pulse-contour monitoring devices and pulmonary artery catheters, which enable therapeutic interventions targeted at cardiac output, preload, and afterload. Both hemodynamic monitors and ventilators provide time-series data with high temporal resolution, ranging from 125 to 500 Hz. These data allow the development of computational models to guide optimal treatment decisions, including the use of vasoactive drugs and fluid therapy^[2].

A promising advancement is the use of wearable devices (WD) to monitor vital parameters and detect clinical deterioration. Typically, vital signs are monitored intermittently in hospital wards (e.g., every 8 h), which may result in missed episodes of clinical deterioration in high-risk patients. In contrast, WDs allow continuous data collection, potentially reducing the necessity for ICU admissions and facilitating high-level monitoring in standard wards or even at home. WD could also be employed to replace parts of the traditional preoperative assessment, such as cardiovascular fitness assessment, relying on data collected by patients at home without direct clinician supervision. Another advantage of WD is that they enable patient mobility without the discomfort of being tethered to stationary monitors. In general, further studies are needed to assess and validate the role of WD in the perioperative setting, also considering how their low cost is facilitating their adoption^[7-11].

The electronic health record (EHR) system typically manually records monitoring data, clinical evaluations, radiology, and laboratory data. Originally designed as a tool for clinical documentation and billing, the EHR has evolved into a valuable tool for clinical research and quality improvement^[12].

Prior to the widespread adoption of modern EHR systems, most epidemiological data were derived from multicenter registries or healthcare claims databases, while other sources of data came from administrative databases for reimbursement purposes. This was particularly relevant when considering rare events. Singapore's SingHealth Perioperative and Anesthesia Subject Area Registry (PASAR), one of these registries, had collected data on approximately 153,312 patient admissions, spanning from preoperative evaluation to postoperative treatment^[13].

More recently, the Multicenter Perioperative Outcomes Group (MPOG) has collected over 489 million medical records and 10.7 million anesthesia records from dozens of hospitals. The achieved numbers indicate the importance of multicentric collaborations in research and quality improvement projects. These datasets allowed studying postoperative outcomes such as opioid use, the efficiency of multimodal pain management strategies, and the efficacy of regional anesthesia^[14].

While these registries were created to collect data for scientific research and quality purposes, EHRs were designed primarily to document clinical information for internal use and thus may lack the quality, standardization, and harmonization needed for research use. Accordingly, we need to improve the quality of EHR data to ensure reproducibility, external validity, and data harmonization among different centers.

Data accuracy and consistency: automatic labeling of artifacts and false readings

A model can only be as accurate as the data on which it is based. Consequently, the quality of the data is

MONITORING SYSTEMS		
OR	ICU	TELEMETRY
<ul style="list-style-type: none"> • Bispectral Index (BIS) • Ventilator Curves • EtCO₂ • Peripheral Saturation • Invasive Pressure • Vigileo • Central Vein Line (CVP) 	<ul style="list-style-type: none"> • Bispectral Index (BIS) • Ventilator Curves • EtCO₂ • Peripheral Saturation • PiCCO • Swan-Ganz • Central Vein Line (CVP) • Nutrivent 	<ul style="list-style-type: none"> • Wearable Devices • EtCO₂ • Peripheral Saturation

Figure 2. Monitoring system used in the hospitals to collect data.

crucial for allowing validation, reliability, and the concrete application of any artificial intelligence (AI) system in clinical practice. Different manufacturers, device specifications, and software versions within each class of devices result in differences in quality, resolution, and dictionary of collected data, as well as compatibility issues^[12]. Furthermore, the large volume of data, considering thousands of physiological observations per anesthetic record, can further complicate the analytical procedure^[1].

Physiological monitoring devices, such as arterial lines or pulse oximetry, are prone to mechanical distortions or interferences, leading to inaccurate readings. For instance, catheter damping can lead to an underestimation of blood pressure, while resonance effects can cause an overestimation^[12]. Very low or very high values are often caused by incorrect readings, detachment, and distortion, and while readily recognized by the perioperative team, these alterations can be difficult to recognize later in time when considering massive amounts of data. In other words, while clinical staff can often identify artifacts during real-time monitoring, retrospective detection of inaccurate reading - known as labeling - is labor-intensive and resource-consuming. Advanced algorithms can help mitigate these inaccuracies by filtering out noise and detecting the artifacts generated during data collection. This can be a significant contribution to the advancement of the analysis of high-frequency data^[3].

Another issue is related to the prevalence of missing or incomplete data, which constitutes a significant challenge^[15,16]. They may result in the introduction of uncontrolled biases, particularly when used in clinical research, leading to reduced performance of predictive algorithms. Missing data in EHR may arise primarily due to (1) technical issues, where the data does not appear in the system due to device errors or faults in data transmission; and (2) clinical issues, where the data are not entered into the EHR because they are considered unnecessary by the physicians or due to time constraints. Missing data can be classified into three categories, which influence the choice of analysis strategies:

- Missing completely at random (MCAR): where there is no systemic pattern behind the missing values, which could be related to observed or non-observed data.
- Missing at random (MAR): where the missing values are related to the observed data, not to the unobserved. Here, the probability of missingness is related to observed data. An example is when missing data or inaccurate monitoring data are present in less critical patients due to human intervention focused on more critical cases.
- Missing not at random (MNAR): refers to situations where the missing values arise from a consistent bias associated with unobserved data, which can influence the results.

Multiple studies have shown the impact of missing data on perioperative care and how these significantly impact the accuracy and further reliability of perioperative research, as well as patient recovery. In a study conducted by DeCrane *et al.*, incomplete datasets introduced biases in postoperative cognitive dysfunction (POCD), leading to misinterpretation of the true estimation of the associated risk factors related to POCD prevalence^[17]. Similarly, a recent study by Aziz *et al.* showed how missing data hinder the identification of risk factors in postoperative complications, which in turn affects the clinical decision making and patient outcomes^[18].

Selecting an appropriate imputation method is critical, as simple removal of records with missing values leads to data loss. Several approaches have been developed:

(a) Simple imputation methods:

These methods substitute the missing data points with single statistical estimates.

- Mean/median/mode imputation: These simple imputation methods use the mean, median, or mode to fill in the missing values. While computationally efficient, these methods reduce variance in the dataset and fail to maintain the relations between variables^[19].
- Forward fill (FFILL): This method replaces a missing value with the last non-missing value. Suitable for time-series physiological data and still computationally efficient, it may introduce bias in longer gaps^[20].
- Last observation carried forward (LOCF): As the name implies, this method uses the last known non-missing value to fill in all the gaps in the data. Effective for short-term missing intervals^[20].

(b) Advanced statistical and machine learning (ML) methods:

Advanced statistical methods fill in the data by estimating the uncertainty associated with the missing values, while ML approaches use predictive modeling to approximate the missing values^[21].

- Multiple imputation by chained equations (MICE): creates multiple imputations over a single imputation to account for statistical uncertainty^[22].
- K-nearest neighbours (k-NN) imputation: imputes missing values by identifying the k most similar instances (called “neighbors”) and using their value (mean, median, or most frequent value) for imputation^[23].
- Random forest (RF) imputation: demonstrates reliable performance for mixed-type data with the ability to capture non-linear relationships^[24].

(c) Deep learning approaches:

- Generative adversarial networks (GANs): operate on the principle of generative modeling, learning probabilistic data distributions through adversarial training with deep neural networks^[25]. It shows promise for complex multivariate time-series data^[26].
- Recurrent neural networks (RNNs): a neural network that learns from past data to estimate weights without requiring domain knowledge to predict new data^[27]. This model excels at capturing temporal

dependencies in physiological data^[28].

- Variational autoencoders (VAEs): provide uncertainty quantification alongside imputation, which is crucial for clinical decision making^[29].

While imputing missing values with summary statistics is a simple and straightforward approach, the method is often inadequate for the more complex data, including intraoperative data^[30]. No single rule applies, so the choice of imputation depends on the pattern of missingness, the complexity of the dataset, the computational requirements, and the intended use of data^[31]. For real-time applications, summary statistics methods can be used for computational efficiency, while for research applications, other approaches provide better accuracy in quantifying uncertainty^[32]. When the proportion of missing data approaches 80%-90%, it is advisable to exclude the variable, since any imputation technique will introduce bias.

Data standardization and harmonization: challenges in interoperability and external validity

Data standardization is pivotal for consistent data collection across centers^[33]. In perioperative medicine, some efforts have been made to promote data standardization, such as the development of a minimum set of data for comprehensive geriatric assessments^[34].

Standardization allows merging data from multiple sources, including EHRs from different manufacturers, imaging and monitoring systems. It works by applying a common data structure, such as a predefined data dictionary, consistent units of measure, and predefined sampling rates. Harmonization goes a step further by aligning data from many sources for integration and analysis^[35]. To answer these needs, the Health Level Seven (HL7) standards and Digital Imaging And Communications In Medicine (DICOM) were proposed to grant interoperability^[36]. In 2011, HL7 created the Fast Healthcare Interoperability Resources (FHIR), a new standard aimed at improving how healthcare information is shared, using technologies such as Representational State Transfer (REST) architecture, application programming interfaces (APIs), XML format, JSON format, and Open Authorization tools^[37]. Similarly, the DICOM standard is designed to maintain interoperability in medical imaging across hospitals. In addition to creating standards for storage, DICOM also ensures uniformity in metadata and imaging acquisition protocols^[38].

As reported by Guglielminotti *et al.* (2015), consistency in reporting and methodology in multivariable analysis for prognostic observational studies is needed for reproducing research findings and increasing the reliability of research^[39]. Data integration and harmonization have also been reported to enhance the prediction of postoperative cardiac events from decision support systems^[40]. Standardization facilitates international data collection and enhances the quality of care by enabling benchmarking across institutions. An example is postoperative pain^[41].

Medical records include specific data types, from clinical observations to insurance claims, which vary widely in their organization, structure, and dictionary. Consequently, CDMs were created to merge data from sources and to store information systematically using predefined syntax^[42,43]. Several CDMs have been developed; among these, the most used are the observational medical outcomes partnership (OMOP), the sentinel CDM (SCDM), the national patient-centered clinical research network CDM (PCORnet CDM), and Informatics for Integrating Biology in the Bedside (i2b2)^[44-48].

In particular, OMOP has gained the largest diffusion. OMOP has been successfully employed in key projects such as the European health data and evidence network (EHDEN), which aims to harmonize patient data across European countries to improve patient care and medical research^[43]. It demonstrated

superior performance due to the extensive vocabulary, which allows us to handle complex, heterogeneous data in healthcare^[49]. Table 1 presents the most widely used CDMs proposed to enhance the quality of data collection in perioperative care.

Health data are standardized to a CDM through an extract, transform, and load (ETL) process, which is defined by multidisciplinary teams comprising clinicians, data engineers, and data managers. In 2017, Ong *et al.* isolated 24 technical problems, categorized into six core topics, encompassing challenges from data sources (e.g., heterogeneity and accessibility) to data management (e.g., code maintenance and sharing)^[50].

Standardization of temporal resolution and image data

High-frequency data collected by monitoring devices have temporal resolutions on the order of milliseconds, reaching up to 500 Hz. This is necessary to visualize waveforms. Filtering techniques, derived from physics and mathematics, include low-pass and high-pass filters. These are often applied to preserve the most critical information and to rule out noise^[3]. Filtering, especially low-pass filters, has traditionally been used to reduce noise and improve data quality. With the advent of AI, filtering is even more necessary to handle data analysis even under high-noise conditions.

Several techniques have been developed to reduce noise in pictures, achieving sharper images, a principle that can also apply to complex medical signals. As for handling of missing data, the choice of filters depends on the type of noise and data addressed. Some techniques are:

- Low-Pass Filters: remove high-frequency noises while preserving low-frequency features such as general shape and contrast.
- High-Pass Filters: the opposite of low-pass filters.
- Median Filters: preserves edges using the median values.
- Mean Filters: a simple method used to remove less severe noise by taking the average pixel values.
- Weiner Filter: an adaptive filter that minimizes the difference between the estimated and original signal.
- Bilateral Filter: preserves edges by replacing the intensity of a pixel with the weighted average of the intensities of its neighboring pixels.

For medical images, specific types of noise and appropriate filters are:

- Gaussian noise: follows a standard bell-shaped curve, best addressed by the Wiener filter.
- Salt and Pepper noise: appears as black and white pixels on an image, and is effectively eliminated by the Median Filter.
- Speckle noise: exhibits a granular pattern, and needs Bilateral filters^[51,52].

The performance of these filters can be assessed using the peak signal-to-noise ratio (PSNR) metric.

Convolved neural networks (CNNs) have emerged as leaders in the analysis of healthcare imaging data, achieving significant performance even in the presence of significant noise^[53]. An example is ClarifyNet, an end-to-end trainable CNN model developed by Susladkar *et al.* for dehazing photos^[54]. ClarifyNet was originally developed for computer vision applications and not specifically for perioperative care. Nonetheless, the underlying principles of noise reduction and image enhancement using high-pass (to detect sharp edges and finer details) and low-pass filters (for color and contrast) are highly relevant to noise reduction and image enhancement. CNNs have been used for noise and artifacts removal and have outperformed traditional techniques in published studies. They have been used to eliminate eye blink artifacts from electroencephalography signals^[55], while in the context of ultra-high-resolution photon-counting detector computed tomography (UHR-PCD-CT), they achieved up to 89% performance in noise reduction^[56].

Table 1. Description of commonly adopted CDMs

CDMs	Funding agency	Mission	Characteristic ^[44]	Advantages
OMOP CDM ^[45]	Reagan Udall Foundation for the FDA (RUF)	Systematic analysis of disparate observational databases using a common format and vocabularies for a standardized model for data sharing	Java-based toolset for user queries; standard vocabulary EAV style	Open source; extensive terminologies; global collaborations; highly standardized
SCDM ^[46]	US Food and Drug Administration (FDA)	Creation and operation of a national public health surveillance system to monitor FDA-regulated products	Standard querying mechanism and code library	Secure network of distribution; protect patient confidentiality; analytical flexibility and transparency
PCORnet CDM ^[47]	Patient-Centered Outcomes Research Institute (PCORI)	Standardization of a million data points from diverse clinical information systems into a common format to provide a clear, consistent answer for the same question asked across different systems Based on SCDM	Standard querying mechanism and code library	Protect patient confidentiality; promote multi-site patient-centric research; analyze data quickly; ease of access, use, and distribution
i2b2 ^[48]	National Institutes of Health (NIH) National Centers for Biomedical Computing (NCBC)	Creation of software to help researchers' genomics with clinical data to improve personalized medicine and patient care The goal is to enable clinical researchers to conduct research incorporating genomics and biomedical informatics into clinical research	Modeled on star schema, a central "fact" table containing patient observation surrounded by one or more "dimension" tables providing additional information	Open source; include genomic findings relevant to human health; promote translational research; star schema makes it flexible and fast

CDMs: Common data models; OMOP: observational medical outcomes partnership; EAV: entity-attribute-value; SCDM: sentinel common data model; PCORnet CDM: national patient-centered clinical research network CDM; i2b2: Informatics for Integrating Biology in the Bedside.

Standardized dictionaries

An important aspect of data standardization mentioned above is the use of a standard dictionary as a common language across different centers. An example is the International Classification of Diseases (ICD) coding system, developed by the World Health Organization (WHO). This system uses alphanumeric codes for disease classification and reimbursement purposes^[57]. The ICD has been adopted for recoding diseases and sharing disease data across regions, thereby supporting benchmarking and evidence-based decision making.

The Standard Nomenclature of Medicine Clinical Terms (SNOMED CT) was deployed to provide a standardized clinical dictionary for different EHRs^[58]. In perioperative care, SNOMED CT standardizes the terminology used for surgical procedures, techniques, and complications. On the other hand, the logical observation identifiers names and codes (LOINC) standardizes terminology of clinical observations, including vital parameters and lab results, and is the preferred standard used by HL7 to attain interoperability^[59].

Other standards used include RxNORM for drug delivery systems, providing standardized drug names for pharmacy systems and drug interaction databases^[60]; current procedural terminology (CPT), which serves as the standard language for the communication of healthcare procedures^[61]; and Unified Code For Units Of Measurement (UCUM) for expressing quantities across domains ranging from medicine to business^[62].

There is ongoing collaboration among various organizations to make standards more consistent, interoperable, and user-friendly for both clinicians and researchers. SNOMED, which encodes patient clinical information, must interoperate with LOINC, which covers laboratory results, to ensure comprehensive EHR integration. This is achieved through the Unified Medical Language System (UMLS),

providing semantic mapping and links between terminologies^[63]. There has been ongoing collaboration between the two organizations, SNOMED International and LOINC, for cooperative work in linking the terminologies and reducing redundancy^[64].

Impact of data quality on patient safety and outcomes

Safety and quality are pivotal aspects of perioperative medicine, both of which can be significantly influenced by the quality of collected data^[65]. A study by Fu *et al.* compared the quality of data extracted from two EHR systems in relation to the incidence of postoperative complications. The findings demonstrated that data quality can negatively impact patient outcomes and hinder clinical decision making. Similarly, inconsistent or incomplete documentation may lead to errors in therapeutic management^[66].

A Delphi study investigating the safety indicators in surgical patients showed that 74% of 73 key indicators considered crucial by the experts were related to the care quality, including effective monitoring and communication^[67]. Clear and effective communication is critical in perioperative care, especially during handovers from the operating room to the wards or between different intraoperative teams. The use of formal checklists has been shown to significantly enhance patient safety^[68]. Conversely, a lack of standardization in postoperative handovers has been associated with compromised postoperative care^[69]. Documentation errors are common and can also lead to complications, longer stay, and lower quality of life. Documentation is not only a clinical necessity but also a legal requirement. In a study on hand trauma cases, only 18.3% of the perioperative data were available for extraction, with some procedures exhibiting up to 38% missing data^[68]. High-quality documentation ensures that all relevant information is available for clinical decision making^[70], whereas omissions, errors, and inconsistencies can impair care delivery and complicate the investigation of adverse events^[71].

Such documentation and quality issues are also prevalent in open datasets. Initiatives like the Perioperative Risk Assessment Dataset (PRAD) integrate multi-view clinical data with pairwise comparison labels to improve the reliability of surgical risk prediction models^[72]. However, the effective use of these datasets for research is often limited by poor data quality, including inconsistencies and non-standardized formats^[73].

Challenges and future directions

As reported above, further efforts to ensure compatibility between different platforms are needed^[74]. One of the main challenges is related to regulations and privacy issues across countries, which hinder the harmonization of data from different jurisdictions^[75]. Regional differences in healthcare practice and in population can also affect the harmonization process. These can lead to ethical issues and socioeconomic bias, resulting in models being trained on incomplete, biased datasets that underrepresent certain populations. For example, a model trained on data from the US Veteran Health Administration may not generalize well to populations in other countries. To facilitate global intensive care data collection, initiatives such as the massive BlendedICU dataset have been proposed. The BlendedICU dataset merges data from prominent open critical care databases, including Amsterdam UMCdb, eICU, HiRID, and MIMIC-IV, and harmonizes them using the OMOP CDM format^[76]. Similarly, the INDICATE initiative by ESICM is designed to create a standardized ICU dataset across a network of European ICUs.

The creation process of these datasets reveals significant real-world challenges. First, the source databases exhibit high variability in data collection methods, recording formats, and treatment policies, reflecting diverse clinical practices and patient populations worldwide. To minimize bias and errors, merging these datasets requires meticulous expert mapping - a lengthy and resource-intensive task. Another example is the Chinese Anesthesiology Benchmark (CAB), a database developed to evaluate medical LLMs in a non-English context. Findings showed that even the top-performing models struggled to achieve clinician-level

accuracy regarding safety. This challenge likely stems from the lack of high-quality, domain-specific datasets in non-English languages, posing an additional obstacle for multicentric datasets^[77].

Among future challenges, we should also consider the educational initiatives needed to bridge the gap between data science and clinical practice. A solid clinical understanding is essential to effectively leverage the vast amount of available data, while a strong grasp of data science is equally important to facilitate the adoption of data-driven tools and technologies^[1]. AI is increasingly integrated across medical fields, including anesthesiology, where it enhances patient outcomes by enabling real-time risk prediction and personalized perioperative care. As AI becomes a routine part of clinical practice, training healthcare staff to manage AI systems and to generate and maintain high-quality data is crucial for improving patient outcomes^[78]. The METRIC framework, proposed by Schwabe *et al.*, is a 15-dimensional checklist designed to evaluate medical training data and could serve this purpose. This framework includes clusters that assess data quality dimensions such as Measurement process, Timeliness, Representativeness, Informativeness, and Consistency, enabling thorough evaluation of data prior to their use in training predictive models^[79].

DISCUSSION

In this review, we emphasize the principle that reliable, high-quality data are fundamental to perioperative care. From preoperative assessment to intraoperative monitoring and post-discharge care, the quality of data directly influences our ability to detect early warning signs of deterioration, personalize treatment plans, and benchmark performance and quality across institutions.

The exponential growth of perioperative data presents unprecedented opportunities but also substantial challenges. While the volume and variety of available data are expanding rapidly, the quality and reliability of these data remain inconsistent across institutions and systems. Anesthesiologists and other perioperative clinicians should be familiar with strategies to improve data quality, such as artifact filtering, imputation methods, standardized dictionaries, and CDMs.

Considerations for real-world application

This review highlights the need for standardized vocabularies (SNOMED CT, LOINC) and harmonization frameworks to assure data quality and facilitate collaboration across institutions. However, implementation remains challenging due to differences in institutional capabilities, regulatory requirements, and resource availability. The adoption of standard data models, particularly the OMOP CDM, represents a crucial step toward achieving interoperability across diverse data systems.

There is no universal solution to achieving high data quality and harnessing its full potential for efficient, sustainable data collection. Each center must weigh factors such as computational complexity, implementation costs, and optimal workflow integration, recognizing that different hospitals may require tailored approaches to data quality management.

We propose that this process can be enhanced through the formation of interdisciplinary teams comprising data scientists, informaticians, and healthcare professionals such as doctors and nurses. In this context, it is imperative to structure the training and education of healthcare professionals in data science, data analysis, and data quality management. Increasing awareness of international standards and regulatory frameworks within the medical community is equally important. Moreover, fostering and effectively disseminating international collaborations should be a priority.

Limitations of this review

This study did not include a formal quality evaluation of the reviewed studies, in line with the methodology of a scoping review. Although the initial search covered Google Scholar and Scopus, we ultimately relied on PubMed to maintain a focused and manageable scope specifically on perioperative data quality. This approach may have limited the comprehensiveness of literature identification and selection. Additionally, restricting sources to English-language publications may have excluded relevant non-English literature. Nonetheless, we think that the references provided by our scoping reviewer provide a solid foundation for understanding the current landscape of data quality in the perioperative context.

Conclusions

Data quality is a cornerstone for advancing clinical quality, patient safety, and research in perioperative care. Amid the ongoing data revolution, clinicians and researchers have access to an ever-increasing volume of data. This review underscores the importance of robust data cleaning, effective handling of missing data, and the adoption of standardization and harmonization strategies as critical components for both clinical care and research. Future initiatives should prioritize promoting standards, unified data formats and dictionaries, improving validation methods, and ensuring compliance with privacy and security regulations.

DECLARATIONS

Authors' contributions

Conducted the literature review and prepared the initial draft: Greco M, Bose I, Lupo Pasinetti B

Critically revised the manuscript and provided expert guidance: Greco M, Cecconi M

All authors approved the final version.

Availability of data and materials

Not applicable.

Financial support and sponsorship

None.

Conflicts of interest

All authors declared that there are no conflicts of interest.

Ethical approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Copyright

© The Author(s) 2025.

REFERENCES

1. Mathis MR, Dubovoy TZ, Caldwell MD, Engoren MC. Making sense of big data to improve perioperative care: learning health systems and the multicenter perioperative outcomes group. *J Cardiothorac Vasc Anesth*. 2020;34:582-5. DOI PubMed PMC
2. Zhu Y, Liu X, Li Y, Yi B. The applications and prospects of big data in perioperative anesthetic management. *Anesthesiol Perioper Sci*. 2024;2:30. DOI
3. Awrahman BJ, Aziz Fatah C, Hamaamin MY. A review of the role and challenges of big data in healthcare informatics and analytics. *Comput Intell Neurosci*. 2022;2022:5317760. DOI PubMed PMC
4. Saugel B, Hoppe P, Khanna AK. Automated continuous noninvasive ward monitoring validation of measurement systems is the real challenge. *Anesthesiology*. 2020;132:407-10. DOI PubMed

5. Boer C, Touw HR, Loer SA. Postanesthesia care by remote monitoring of vital signs in surgical wards. *Curr Opin Anaesthesiol*. 2018;31:716-22. DOI PubMed
6. Walsh C, Zargarani D, Patel N, et al. Practical considerations and successful implementation of vital signs monitoring. *J Med Internet Res*. 2021;23:e14042. DOI PubMed PMC
7. Breteler MJM, KleinJan EJ, Dohmen DAJ, et al. Vital signs monitoring with wearable sensors in high-risk surgical patients a clinical validation study. *Anesthesiology*. 2020;132:424-39. DOI PubMed
8. Syversen A, Dosis A, Jayne D, Zhang Z. Wearable sensors as a preoperative assessment tool: a review. *Sensors*. 2024;24:482. DOI PubMed PMC
9. Angelucci A, Greco M, Canali S, et al. Fitbit data to assess functional capacity in patients before elective surgery: pilot prospective observational study. *J Med Internet Res*. 2023;25:e42815. DOI PubMed PMC
10. Greco M, Angelucci A, Avidano G, et al. Wearable health technology for preoperative risk assessment in elderly patients: the WELCOME study. *Diagnostics*. 2023;13:630. DOI PubMed PMC
11. Amin T, Mobbs RJ, Mostafa N, Sy LW, Choy WJ. Wearable devices for patient monitoring in the early postoperative period: a literature review. *Mhealth*. 2021;7:50. DOI PubMed PMC
12. Abdullah HR, Lim DYZ, Ke Y, Salim NNM, Lan X, Dong Y, et al. The SingHealth Perioperative and Anesthesia Subject Area Registry (PASAR), a large-scale perioperative data mart and registry. *Korean J Anesthesiol*. 2024;77:58-65. DOI PubMed PMC
13. Müller-Wirtz LM, Volk T. Big data in studying acute pain and regional anesthesia. *J Clin Med*. 2021;10:1425. DOI PubMed PMC
14. Ahmed A, Xi R, Hou M, Shah SA, Hameed S. Harnessing big data analytics for healthcare: a comprehensive review of frameworks, implications, applications, and impacts. *IEEE Access*. 2023;11:112891-928. DOI
15. Manias G, Azqueta-Alzúaz A, Damiani A, et al. An enhanced standardization and qualification mechanism for heterogeneous healthcare data. *Stud Health Technol Inform*. 2023;302:153-4. DOI PubMed
16. Dash S, Shakyawar SK, Sharma M, Kaushik S. Big data in healthcare: management, analysis and future prospects. *J Big Data*. 2019;6:54. DOI
17. DeCrane SK, Sands LP, Young KM, DePalma G, Leung JM. Impact of missing data on analysis of postoperative cognitive decline (POCD). *Appl Nurs Res*. 2013;26:71-5. DOI PubMed PMC
18. Aziz KT, Nayar SK, LaPorte DM, Ingari JV, Giladi AM. Impact of missing data on identifying risk factors for postoperative complications in hand surgery. *Hand*. 2022;17:1257-63. DOI PubMed PMC
19. Schafer JL, Graham JW. Missing data: our view of the state of the art. *Psychol Methods*. 2002;7:147-77. PubMed
20. National Research Council. The prevention and treatment of missing data in clinical trials. Washington, D.C.: National Academies Press; 2010. DOI
21. Liu M, Li S, Yuan H, et al. Handling missing values in healthcare data: a systematic review of deep learning-based imputation techniques. *Artif Intell Med*. 2023;142:102587. DOI PubMed
22. Azur MJ, Stuart EA, Frangakis C, Leaf PJ. Multiple imputation by chained equations: what is it and how does it work? *Int J Methods Psychiatr Res*. 2011;20:40-9. DOI PubMed PMC
23. Zhang S. Nearest neighbor selection for iteratively kNN imputation. *J Syst Softw*. 2012;85:2541-52. DOI
24. Stekhoven DJ, Bühlmann P. MissForest - non-parametric missing value imputation for mixed-type data. *Bioinformatics*. 2012;28:112-8. DOI PubMed
25. Aggarwal A, Mittal M, Battineni G. Generative adversarial network: an overview of theory and applications. *Int J Inf Manag Data Insights*. 2021;1:100004. DOI
26. Yoon J, Jordon J, van der Schaar M. GAIN: missing data imputation using generative adversarial nets. *arXiv* 2018; arXiv:1806.02920. Available from: <https://doi.org/10.48550/arXiv.1806.02920>. [Last accessed on 28 Jul 2025]
27. Haliduola HN, Bretz F, Mansmann U. Missing data imputation in clinical trials using recurrent neural network facilitated by clustering and oversampling. *Biom J*. 2022;64:863-82. DOI PubMed
28. Lipton ZC, Kale DC, Wetzel R. Modeling missing data in clinical time series with RNNs. *arXiv* 2016; arXiv:1606.04130. Available from: <https://doi.org/10.48550/arXiv.1606.04130>. [Last accessed on 28 Jul 2025]
29. Roskams-Hieter B, Wells J, Wade S. Leveraging variational autoencoders for multiple data imputation. In: Machine Learning and Knowledge Discovery in Databases: Research Track. ECML PKDD 2023. Springer, Cham; 2023. pp. 491-506. DOI
30. Li J, Guo S, Ma R, et al. Comparison of the effects of imputation methods for missing data in predictive modelling of cohort study datasets. *BMC Med Res Methodol*. 2024;24:41. DOI PubMed PMC
31. van Buuren S. Flexible imputation of missing data. 2nd Edition. CRC Press; 2018. DOI
32. Luo Y. Evaluating the state of the art in missing data imputation for clinical data. *Brief Bioinform*. 2022;23:bbab489. DOI PubMed PMC
33. Ahmadian L, Cornet R, Kalkman C, de Keizer NF. Development of a national core dataset for preoperative assessment. *Methods Inf Med*. 2009;48:155-61. DOI PubMed
34. Lodge M, Aitken R, Chong YH, Thillainadesan J. Development of a minimum clinical dataset for preoperative comprehensive geriatric assessment using a modified Delphi technique. *Australas J Ageing*. 2024;43:733-9. DOI PubMed PMC
35. Plebani M. Harmonization in laboratory medicine: the complete picture. *Clin Chem Lab Med*. 2013;51:741-51. DOI PubMed
36. Lareyre F, Behrendt CA, Chaudhuri A, Ayache N, Delingette H, Raffort J. Big data and artificial intelligence in vascular surgery: time for multidisciplinary cross-border collaboration. *Angiology*. 2022;73:697-700. DOI PubMed

37. Vorisek CN, Lehne M, Klopfenstein SAI, et al. Fast healthcare interoperability resources (FHIR) for interoperability in health research: systematic review. *JMIR Med Inform*. 2022;10:e35724. DOI PubMed PMC
38. Larobina M. Thirty years of the DICOM standard. *Tomography*. 2023;9:1829-38. DOI PubMed PMC
39. Guglielminotti J, Dechartres A, Mentré F, Montravers P, Longrois D, Laouénan C. Reporting and methodology of multivariable analyses in prognostic observational studies published in 4 Anesthesiology Journals: a methodological descriptive review. *Anesth Analg*. 2015;121:1011-29. DOI PubMed
40. Kim RB, Alge OP, Liu G, et al. Prediction of postoperative cardiac events in multiple surgical cohorts using a multimodal and integrative decision support system. *Sci Rep*. 2022;12:11347. DOI PubMed PMC
41. Zaslansky R, Chapman CR, Rothaug J, et al. Feasibility of international data collection and feedback on postoperative pain data: proof of concept. *Eur J Pain*. 2012;16:430-8. DOI PubMed
42. Ahmadi N, Zoch M, Kelbert P, et al. Methods used in the development of common data models for health data: scoping review. *JMIR Med Inform*. 2023;11:e45116. DOI PubMed PMC
43. Reinecke I, Zoch M, Reich C, Sedlmayr M, Bathelt F. The usage of OHDSI OMOP - a scoping review. *Stud Health Technol Inform*. 2021;283:95-103. DOI PubMed
44. Weeks J, Pardee R. Learning to share health care data: a brief timeline of influential common data models and distributed health data networks in U.S. Health Care Research. *EGEMS*. 2019;7:4. DOI PubMed PMC
45. Standardized data: the OMOP common data model. Available from: <https://www.ohdsi.org/data-standardization/>. [Last accessed on 28 Jul 2025].
46. Sentinel common data model. Available from: <https://www.sentinelinitiative.org/methods-data-tools/sentinel-common-data-model>. [Last accessed on 28 Jul 2025].
47. PCORnet® common data model. Available from: <https://pcornet.org/data/common-data-model/>. [Last accessed on 28 Jul 2025].
48. i2b2. Available from: <https://www.i2b2.org/about/index.html>. [Last accessed on 28 Jul 2025].
49. Garza M, Del Fiol G, Tenenbaum J, Walden A, Zozus MN. Evaluating common data models for use with a longitudinal community registry. *J Biomed Inform*. 2016;64:333-41. DOI PubMed PMC
50. Ong T, Pradhananga R, Holve E, Kahn MG. A framework for classification of electronic health data extraction-transformation-loading challenges in data network participation. *EGEMS*. 2017;5:10. DOI PubMed PMC
51. Akbar SA, Verma A. Analyzing noise models and advanced filtering algorithms for image enhancement. *arXiv* 2024; arXiv:2410.21946. Available from: <https://doi.org/10.48550/arXiv.2410.21946>. [Last accessed on 28 Jul 2025].
52. Abdallah Y, Abdelhamid A, Elarif T, Salem ABM. Intelligent techniques in medical volume visualization. *Procedia Comput Sci*. 2015;65:546-55. DOI
53. Sarvamangala DR, Kulkarni RV. Convolutional neural networks in medical image understanding: a survey. *Evol Intell*. 2022;15:1-22. DOI PubMed PMC
54. Susladkar O, Deshmukh G, Nag S, et al. ClarifyNet: a high-pass and low-pass filtering based CNN for single image dehazing. *J Syst Archit*. 2022;132:102736. DOI
55. Jurczak M, Kołodziej M, Majkowski A. Implementation of a convolutional neural network for eye blink artifacts removal from the electroencephalography signal. *Front Neurosci*. 2022;16:782367. DOI PubMed PMC
56. Huber NR, Ferrero A, Rajendran K, et al. Dedicated convolutional neural network for noise reduction in ultra-high-resolution photon-counting detector computed tomography. *Phys Med Biol*. 2022;67:175014. DOI PubMed PMC
57. WHO. International statistical classification of diseases and related health problems (ICD). Available from: <https://www.who.int/standards/classifications/classification-of-diseases>. [Last accessed on 28 Jul 2025].
58. SNOMED International. What is SNOMED CT? Available from: <https://www.snomed.org/what-is-snomed-ct>. [Last accessed on 28 Jul 2025].
59. LOINC. About LOINC. Available from: <https://loinc.org/about/>. [Last accessed on 28 Jul 2025].
60. RxNorm. Available from: <https://www.nlm.nih.gov/research/umls/rxnorm/index.html>. [Last accessed on 28 Jul 2025].
61. CPT®. Available from: <https://www.ama-assn.org/practice-management/cpt>. [Last accessed on 28 Jul 2025].
62. UCUM. Available from: <https://ucum.org/>. [Last accessed on 28 Jul 2025].
63. Bodenreider O. Issues in mapping LOINC laboratory tests to SNOMED CT. *AMIA Annu Symp Proc*. 2008;2008:51-5. PubMed PMC
64. LOINC. SNOMED International. Available from: <https://loinc.org/collaboration/snomed-international/>. [Last accessed on 28 Jul 2025].
65. Wacker J. Measuring and monitoring perioperative patient safety: a basic approach for clinicians. *Curr Opin Anaesthesiol*. 2020;33:815-22. DOI PubMed PMC
66. Fu S, Wen A, Schaeferle GM, et al. Assessment of data quality variability across two EHR systems through a case study of post-surgical complications. *AMIA Jt Summits Transl Sci Proc*. 2022;2022:196-205. PubMed PMC
67. Nyberg A, Jirwe M, Fagerdahl A, Otten V, Haney M, Olofsson B. Perioperative patient safety indicators - a Delphi study. *J Clin Nurs*. 2025;34:1351-63. DOI PubMed PMC
68. Cook H, Aggarwal A, Kanapathy M, Davison E, Ioannidi L. 1009 Improving accuracy and extractability of electronic operative documentation data in a hand trauma unit. *Br J Surg*. 2023;110:znad258.167. DOI
69. Abraham J, Meng A, Sona C, Wildes T, Avidan M, Kannampallil T. An observational study of postoperative handoff standardization failures. *Int J Med Inform*. 2021;151:104458. DOI PubMed

70. Hofer IS, Cheng D, Grogan T. A retrospective analysis demonstrates that a failure to document key comorbid diseases in the anesthesia preoperative evaluation associates with increased length of stay and mortality. *Anesth Analg.* 2021;133:698-706. [DOI](#) [PubMed](#) [PMC](#)
71. Smith JD, Lemay K, Lee S, et al. Medico-legal issues related to emergency physicians' documentation in Canadian emergency departments. *CJEM.* 2023;25:768-75. [DOI](#) [PubMed](#) [PMC](#)
72. Li X, Zhan Y, Zhao Y, et al. A perioperative risk assessment dataset with multi-view data based on online accelerated pairwise comparison. *Inf Fusion.* 2023;99:101838. [DOI](#)
73. Lim L, Lee HC. Open datasets in perioperative medicine: a narrative review. *Anesth Pain Med.* 2023;18:213-9. [DOI](#) [PubMed](#) [PMC](#)
74. Mohammed F, Naaz M. Big data analytics: challenges and applications in healthcare. *Int J Sci Res.* 2023;12:834-8. [DOI](#)
75. Pezoulas VC, Fotiadis DI. The pivotal role of data harmonization in revolutionizing global healthcare: a framework and a case study. *Conn Health Telemed* 2024;3:300004. [DOI](#)
76. Oliver M, Allyn J, Carencotte R, Allou N, Ferdynus C. Introducing the BlendedICU dataset, the first harmonized, international intensive care dataset. *J Biomed Inform.* 2023;146:104502. [DOI](#) [PubMed](#)
77. Zhou B, Zhan Y, Wang Z, et al. Benchmarking medical LLMs on anesthesiology: a comprehensive dataset in Chinese. *IEEE Trans Emerg Top Comput Intell.* 2025;9:3057-71. [DOI](#)
78. Chae D. Data science and machine learning in anesthesiology. *Korean J Anesthesiol.* 2020;73:285-95. [DOI](#) [PubMed](#) [PMC](#)
79. Schwabe D, Becker K, Seyferth M, Klab A, Schaeffter T. The METRIC-framework for assessing data quality for trustworthy AI in medicine: a systematic review. *NPJ Digit Med.* 2024;7:203. [DOI](#) [PubMed](#) [PMC](#)