Journal of Surgery
Chen X, et al. J Surg 10: 11261
www.doi.org/10.29011/2575-9760.11261
www.gavinpublishers.com

Review Article

Multimodal Data Fusion-Based Risk Assessment Models and Clinical Decision Support Systems for Intraoperative Acquired Pressure Injuries

Xiaojun Chen, Shufen Liao, Pin Wang, Guilan Huang, Jinyan Li, Shuyan Zeng, Qiuyi Ouyang, Qin Guo, Shiyun Qin, Fengqiu Gong*

Department of Operating Room, The First Affiliated Hospital, Sun Yat-sen University, Guangzhou 510080, Guangzhou, China

***Corresponding author:** Fengqiu Gong, Department of Operating Room, The First Affiliated Hospital of Sun Yat-sen University, Guangzhou 510080, Guangzhou, China

Citation: Chen X, Liao S, Wang P, Huang G, Li J, et al. (2025) Multimodal Data Fusion-Based Risk Assessment Models and Clinical Decision Support Systems for Intraoperative Acquired Pressure Injuries. J Surg 10: 11261 DOI: 10.29011/2575-9760.011261

Received Date: 17 February 2025; **Accepted Date:** 24 February 2025; **Published Date:** 26 February 2025

Abstract

This article reviews the Intraoperatively Acquired Pressure Injuries (IAPIs) risk assessment model based on multimodal data fusion and its clinical decision support system. Intraoperatively acquired pressure injuries refer to skin and soft tissue injuries caused by prolonged positional compression during surgical procedures. The mechanism of these injuries is complex, involving multiple factors such as body position, external pressure, and the patient's physiological state. Multimodal data fusion technology, which integrates heterogeneous data sources including clinical data, imaging data, and biomarkers, can significantly improve the accuracy of risk assessment models. This article provides a detailed introduction to the principles of multimodal data fusion technology, the construction method of the risk assessment model for intraoperatively acquired pressure injuries, and the design and implementation of the clinical decision support system. Research indicates that multimodal data fusion technology excels in predicting the risk of pressure injuries, with the model demonstrating significantly higher precision and recall rates compared to traditional methods. In the future, with the continuous development of technology and the expansion of clinical applications, multimodal data fusion is expected to provide more precise support for clinical decision-making, reduce the incidence of intraoperatively acquired pressure injuries, and improve patient care quality.

Keywords: Clinical Decision Support System; Machine Learning; Intraoperative Acquired Pressure Injuries (Iapis); Multimodal Data Fusion; Risk Assessment Model

Background and Current Status of Intraoperative Acquired Pressure Injuries

Definition and Classification of Intraoperative Acquired Pressure Injuries (IAPIs)

IAPIs refer to skin and soft tissue injuries caused by prolonged positioning or external pressure during surgical procedures. These injuries commonly occur on the operating table, particularly during extended surgeries, where factors such as patient positioning, external pressure, and skin humidity can affect their development. IAPIs can be classified into different grades based on severity, typically assessed using the International Pressure Injury Classification System.

Mechanisms of Intraoperative Acquired Pressure Injuries

The mechanisms underlying IAPIs are complex and primarily related to several factors. Firstly, limited positional changes during surgery can hinder local blood circulation due to prolonged immobility, leading to tissue ischemia and necrosis. Secondly, continuous external pressure can cause mechanical damage to the skin and soft tissues, especially over bony prominences like the sacrum, elbows, and knees. Additionally, the patient's physiological state (e.g., malnutrition, diabetes) and surgical environment (e.g., temperature, humidity) influence the risk of IAPIs [1].

Clinical Manifestations and Diagnosis of Intraoperative Acquired Pressure Injuries

Clinical manifestations of IAPIs typically include local skin redness, swelling, pain, and skin breakdown. The severity of the injury determines the specific symptoms, which may range from skin erythema in early stages to ulcers or deep tissue damage in severe cases. Diagnosis relies on clinical observation and evaluation, considering the patient's medical history and surgical records. Recently, with advancements in information technology, machine learning models based on electronic health records have been applied to predict and assess IAPIs, demonstrating promising predictive performance [2].

Epidemiological Data on Intraoperative Acquired Pressure Injuries

Epidemiological studies indicate significant variations in the incidence of IAPIs across different surgical types and patient populations. A systematic review and meta-analysis reported a wide range of incidence rates from 0.5% to 30% in various studies [3]. Certain high-risk patient groups, such as elderly, obese, or those with comorbidities, are more susceptible to IAPIs. Research also suggests that factors like extended surgical duration, positioning choices, and intraoperative nursing quality are closely associated with the occurrence of IAPIs [4]. In summary, intraoperative acquired pressure injuries represent a complex and multifaceted clinical challenge. A deep understanding of their definition, mechanisms, clinical manifestations, and epidemiological data provides a crucial foundation for establishing clinical decision support systems. This, in turn, can effectively reduce the incidence of IAPIs and enhance patient care quality.

Principles of Multimodal Data Fusion Technology

Overview of Multimodal Data Fusion Technology

Multimodal data fusion is a technology that combines deep learning and machine learning, widely used in medical data analysis and risk assessment. By integrating data from different sources and types, this technology can more comprehensively capture patients' health status and potential risks, thus providing support for clinical decision-making. The core of multimodal data fusion technology lies in its ability to handle heterogeneous data sources, including clinical data, imaging data, and biomarkers. Studies have shown that multimodal data fusion technology can effectively improve the accuracy of prediction models when processing complex medical data. For example, a study used a multimodal data fusion technology model to predict the invasive risk of lung adenocarcinoma, and the results showed that the accuracy of the model reached 88.5%, and the area under the ROC curve (AUC) was 0.957, which was significantly better than traditional single-data source models [5]. Additionally, multimodal data fusion technology has demonstrated its potential in the risk assessment of pressure injuries. By fusing clinical variables and imaging data, the model can identify patients with different risk levels and provide a basis for clinical intervention. Studies have shown that when using a multimodal data fusion technology model for pressure injury risk prediction, the precision and recall rates of the model are significantly higher than traditional methods, indicating its effectiveness and feasibility in clinical applications [6].

Basic Principles of Multimodal Data Fusion

The basic principle of multimodal data fusion lies in integrating data from different sources to extract more comprehensive and accurate information. This process typically includes steps such as data preprocessing, feature extraction, feature fusion, and model training. Specifically, the data preprocessing stage requires cleaning and standardizing data from different modalities to ensure data consistency and comparability. In the feature extraction stage, deep learning models (such as convolutional neural networks) are widely used to extract features from imaging data, while traditional machine learning methods (such as random forests and support vector machines) are often used to process structured clinical data. By fusing these features, DML-GMM can capture complementary information between different modalities, thereby improving the predictive ability of the model. For example, in a study on brain diseases, researchers adopted a multimodal learning framework to fuse MRI and PET imaging data. The results showed that the model performed better in disease diagnosis than single-modality models, with an AUC value of 0.95 [7]. This fusion strategy not only improves diagnostic accuracy but also provides clinicians with a more comprehensive assessment of patients' health.

Applications of Multimodal Data Fusion Technology in Medical Data

The application of multimodal data fusion technology in medical data is increasingly widespread, especially in areas such as disease prediction, risk assessment, and personalized treatment. By integrating multiple data sources, multimodal data fusion technology can provide more precise support for clinical decision-making. In the risk assessment of pressure injuries, the multimodal data fusion technology model successfully identifies high-risk patients by fusing clinical and imaging data. Studies have shown that the model achieves an accuracy rate of 82% in predicting pressure injuries, which is significantly higher than traditional single-data source models [8]. Additionally, multimodal data fusion technology has been applied to the prognostic evaluation of trauma patients. By combining clinical, immunological, and imaging data, the model can effectively predict patients' comorbidity risks and help doctors develop personalized treatment plans [9]. In the diagnosis of brain diseases, multimodal data fusion technology has also demonstrated its strong application potential. By fusing

MRI and clinical data, the model can more accurately identify the pathological features of Alzheimer's disease patients, with an AUC value of 0.92, highlighting its importance in early diagnosis [7]. This multimodal fusion strategy not only improves diagnostic accuracy but also provides clinicians with a more comprehensive assessment of patients' health. In summary, multimodal data fusion technology, as an advanced technology, is gradually changing the way medical data is analyzed with its powerful data processing capabilities and accurate predictive performance. It provides new ideas and methods for clinical decision-making

Construction of a Risk Assessment Model for Intraoperative Acquired Pressure Injuries

Data Collection and Preprocessing

Data collection and preprocessing are crucial first steps in constructing a risk assessment model for intraoperative acquired pressure injuries. According to the literature, the diversity and quality of data directly impact the predictive power and reliability of the model. Studies have shown that using multi-source and multimodal data can better capture the risk patterns of pressure injuries. For instance, Huang et al. (2022) proposed a multimodal fusion-based risk prediction model for sports injuries, utilizing various data such as training load, perceived health status, physiological responses, and physical performance. The results indicated high accuracy in classifying non-injured and minimally injured risks (with an average precision of 0.9932 and a recall rate of 0.9976) [6]. In the study of intraoperative acquired pressure injuries, data preprocessing is equally important. Jiang et al. (2021) conducted a systematic evaluation of machine learning techniques in pressure injury management, highlighting that the quality of data preprocessing directly affects the predictive performance of the model. The study mentioned that data cleaning, standardization, and feature extraction are critical steps to improve model accuracy [10]. Additionally, Zhou et al. (2022) established a pressure injury management information platform. Through the analysis of monitoring data from 578 patients, the platform demonstrated effectiveness in postoperative pressure injury assessment, emphasizing the importance of systematic and continuous data collection and processing [4].

Feature Selection and Feature Engineering

Feature selection and feature engineering are pivotal steps in building an effective risk assessment model. By selecting features relevant to pressure injuries, the predictive power of the model can be significantly improved. Song et al. (2021) extracted 28 clinical features from electronic health record data in their study and achieved efficient prediction of hospital-acquired pressure injuries using a random forest model, with an AUC value reaching 0.94, highlighting the importance of feature selection [2]. In terms of feature engineering, Nakagami et al. (2021) proposed a prediction model based on machine learning that utilizes health data collected by nurses on the first day of admission to successfully identify high-risk patients. This study demonstrates that feature selection and construction not only depend on data availability but also require the integration of clinical experience and practical application scenarios [11]. Additionally, Mottaghi et al. (2022) presented a deep hybrid density neural network model that extracts deep features from motion data through multi-branch convolutional layers, further enhancing the predictive capabilities of the model and emphasizing the significance of feature engineering in complex data processing [12].

Model Development and Training

Model development and training are crucial steps for implementing pressure injury risk assessment. By selecting appropriate machine learning algorithms, the predictive performance of the model can be effectively improved. Song et al. (2021) trained their model using a random forest algorithm on different types of pressure injuries, achieving excellent performance with AUC values of 0.92 and 0.94 on two test sets, respectively [2]. Furthermore, Huang et al. (2022) constructed a multimodal data fusion model using the Extreme Gradient Boosting (XGBoost) algorithm, which demonstrated superior performance over traditional models in classifying non-injured and mildly injured risks, improving average precision and recall rates by 8.2% and 20.3%, respectively [6]. During model training, cross-validation serves as a critical method for evaluating model performance. In their study, Zhou et al. (2022) compared the performance of different models and found that the XGBoost model excelled in handling multimodal data, achieving an AUC value of 0.983. This outstanding performance demonstrates the model's strong adaptability in complex data environments [3]. Additionally, Li et al. (2023) proposed a hybrid variable graphical modeling framework that integrates latent and mixed variables, achieving a balanced accuracy of 0.941. This further validates the effectiveness of model construction [13].

Model Validation and Performance Evaluation

Model validation and performance evaluation are crucial steps to ensure the reliability of risk assessment models. Through systematic evaluation of the model's performance, its effectiveness and limitations in practical applications can be identified. Ma et al. (2024) pointed out in their systematic review that the AUC values of existing pressure injury risk prediction models range from 0.70 to 0.99, indicating variations in predictive ability among different models [3]. Furthermore, Gao et al. (2018) established a new risk assessment model for intraoperative acquired pressure injuries using multivariable logistic regression analysis, with an AUC value of 0.897. This suggests the potential of the model in clinical applications [1]. In the practical application of the model, verifying its applicability across different populations and environments is essential. Li et al. (2023) conducted an external validation of a prediction model for hospital-acquired pressure injuries. The results showed that the model maintained good predictive performance in different clinical scenarios, with an AUC value of up to 0.983. This further demonstrates the stability and reliability of the model [13]. Through these studies, it becomes evident that model validation and performance evaluation are not only necessary steps for constructing effective risk assessment models but also crucial foundations for advancing clinical practice.

Design and Implementation of a Clinical Decision Support System

System Requirements Analysis

Before designing and implementing a risk assessment model and clinical decision support system for intraoperative acquired Pressure Injuries (PI) based on multimodal data fusion, a systematic requirements analysis is essential. According to the literature, intraoperative acquired pressure injuries are a widespread yet preventable issue. However, managing this problem poses challenges due to nursing shortages and insufficient related knowledge [10]. Therefore, the system design must consider how Machine Learning (ML) techniques can enhance the prognosis and diagnostic accuracy of PI, thereby reducing the burden on medical staff. Studies indicate that current applications of ML in PI management primarily focus on risk factor identification, posture detection, and image analysis [10]. Consequently, the system needs to integrate multiple data sources, including preoperative and intraoperative data, to assess patient risk more comprehensively. Research has shown that ML models combining preoperative and intraoperative data excel in predicting postoperative complications, particularly in predicting complications such as pneumonia, acute kidney injury, and deep vein thrombosis, with AUC values exceeding 0.8 [14]. This suggests that the system should have the capability to process and analyze multimodal data to enhance the accuracy of risk assessment. Furthermore, the literature emphasizes the importance of multimodal monitoring in neurocritical care, highlighting the need for comprehensive monitoring of various physiological variables to support clinical decision-making [15]. Hence, the system design should consider effective integration of data from different monitoring devices to provide real-time clinical decision support.

System Architecture Design

The design of the system architecture is a crucial aspect of implementing a clinical decision support system. According to the literature, designing a generic clinical decision support system involves considering the integration and analysis of multi-scale data [16]. This system should be able to extract information from multiple data sources (such as electronic health records, imaging data, and physiological monitoring data) and analyze it using machine learning algorithms. In architectural design, deep learning and multimodal information fusion technology are recognized as effective methods to enhance behavior recognition and skill learning. Studies have shown that a multimodal information fusion architecture based on deep learning has achieved a 98.5% accuracy rate in recognizing the operational skills of interventional surgeons, significantly superior to traditional single data source methods [17]. Therefore, the system architecture should include a data acquisition module, a data processing module, and a decision support module to enable efficient processing and analysis of multimodal data.

Functional Modules of the System

The design of the system's functional modules should revolve around the core requirements of clinical decision support. According to the literature, the application of machine learning techniques in predicting postoperative complications shows promising prospects, especially when integrating preoperative and intraoperative data [14]. Therefore, the system should include the following key functional modules:

- Data Acquisition Module: Responsible for collecting patient information from various sources, such as electronic health records, monitoring devices, and imaging data.
- Data Processing Module: Utilizes machine learning algorithms to clean, integrate, and analyze the collected data to identify potential risk factors.
- Decision Support Module: Provides real-time clinical decision support based on analysis results, assisting medical staff in developing personalized treatment plans.

Furthermore, the literature also indicates that deep learning models demonstrate good performance in the classification of stages of pressure injuries, aiding nurses in more accurately assessing patient risks [18]. Hence, the system should incorporate image analysis capabilities to facilitate early identification and intervention of pressure injuries.

User Interface Design

User interface design is crucial to ensure the system's ease of use and effectiveness. According to the literature, the user interface of a clinical decision support system should be simple and straightforward, capable of intuitively presenting analysis results and suggestions for medical staff to quickly understand and apply [19]. The interface should include the following aspects:

- Data Display: Clearly showcases patients' multimodal data and analysis results, including risk assessments and suggested interventions.

- Interactive Functionality: Allows users to adjust input parameters as needed and view risk assessment results in different scenarios in real-time.
- Feedback Mechanism: Provides a user feedback channel to continuously optimize the system's functionality and user experience.

In summary, the design and implementation of an intraoperative acquired pressure injury risk assessment model and clinical decision support system based on multimodal data fusion require comprehensive consideration of system requirements, architecture design, functional modules, and user interface to ensure its effectiveness and usability in clinical practice.

Clinical Application and Evaluation

Clinical Trial Design and Implementation

In recent years, studies have demonstrated the profound potential of risk assessment models based on multimodal data in the management of trauma patients, especially in terms of clinical trial design and implementation. Moris et al. (2022) conducted a prospective study that utilized clinical, flow cytometry, and serum cytokine data to develop a sparse logistic regression model. This model aimed to predict multiple clinical outcomes for trauma patients, including ventilator-associated pneumonia and acute kidney injury. The study encompassed 179 patients, and the results indicated that the model's Area Under the Curve (AUC) for prediction ranged from 0.70 to 0.91. This significantly underscores the improved accuracy achieved through the integration of multimodal data [9]. Furthermore, Ma et al. (2024) performed a systematic review and meta-analysis evaluating the performance of 99 risk prediction models for pressure injuries across 62 studies. The findings revealed that 32 models exhibited an AUC range of 0.70 to 0.99, while the validation models showed an AUC range of 0.70 to 0.98. This highlights the good predictive performance of these models in identifying high-risk patients [3]. These investigations provide valuable insights for the design of clinical trials, emphasizing the significance of multimodal data in risk assessment.

Evaluation of Clinical Application Effectiveness

In terms of evaluating clinical application effectiveness, risk assessment models based on multimodal data have demonstrated profound performance in prognostic prediction for various diseases. Wang et al. (2024) developed the DeepClinMed-PGM model, which significantly improved the prediction accuracy of disease-free survival for breast cancer patients by integrating clinicopathological and molecular data. In the training cohort, the model achieved AUC values of 0.979, 0.957, and 0.871 for 1-year, 3-year, and 5-year disease-free survival, respectively. In the external testing cohort, the AUC values were 0.851, 0.878, and 0.938 for 1-year, 2-year, and 3-year survival, respectively, indicating the model's consistency and reliability across different cohorts [20]. Simultaneously, Li et al. (2024) developed a multimodal learning system that successfully predicted the natural pregnancy rate of patients with intrauterine adhesions by integrating electronic health records and hysteroscopic images. The model achieved AUC values of 0.967, 0.936, and 0.965 in the training, validation, and testing datasets, respectively, surpassing single-modal methods. This result suggests that models combining multiple data sources possess significant advantages in clinical decision support [21].

User Feedback and System Improvement

User feedback plays a crucial role in the improvement of multimodal data fusion systems. Seo et al. (2023) developed a deep learning model for pressure injury staging, achieving a macro F1 score of 0.8941, which exceeded the average performance of experienced nurses (0.8781). This finding indicates that the deep learning model exhibits high accuracy in classifying pressure injury stages, assisting less experienced nurses in conducting evaluations [18]. By collecting feedback from clinical nurses, researchers can further optimize the model, enhancing its usability and accuracy in practical applications. Additionally, Snoek et al. (2023) proposed a clinical decision model capable of identifying patients with delayed diagnosis of injuries after high-energy trauma. The model achieved a sensitivity of 92.3% and a specificity of 86.4%. This study underscores the importance of clinical decision support systems in improving the management of trauma patients and provides directions for future system improvements [22]. In summary, the intraoperative acquired pressure injury risk assessment model based on DML-GMM multimodal data fusion has demonstrated remarkable performance in clinical applications. Models that combine multiple data sources can significantly improve prediction accuracy and provide strong support for clinical decision-making. Through continuous collection of user feedback and system improvements, these models are expected to play a greater role in future clinical practice.

Future Development and Prospects

Technology Development Trends

With the continuous advancement of medical technology, the application of multimodal data fusion technology based on deep learning in medical image classification and clinical decision support systems is becoming increasingly widespread. Multimodal medical imaging combines information from different imaging modalities, providing a more comprehensive pathological understanding for clinical diagnosis and research. In recent years, deep learning-driven multimodal fusion technology has been recognized as a powerful tool to improve the performance of medical image classification. Studies have shown that input fusion, intermediate fusion (including single-layer fusion, hierarchical fusion, and attention-based fusion), and output fusion are the three main fusion schemes for multimodal classification networks, which have demonstrated good applicability in different multimodal fusion scenarios and application areas [23].

In the field of surgical intervention, there is relatively little research on behavior recognition and skill learning related to interventional doctors' operating skills. Through an innovative deep learning multimodal information fusion architecture, researchers can identify and analyze eight common operational behaviors of interventional doctors. Experimental results show that the overall accuracy of this deep learning fusion architecture reaches 98.5%, which is significantly higher than the performance of traditional machine learning classifiers (93.51%) and single-modal data (90.05%). This achievement indicates that deep learning multimodal information fusion technology has important application potential in enhancing the autonomy and intelligence of surgical robot systems [17]. Deep multimodal fusion technology also demonstrates its importance in disease diagnosis and prognosis. With the rapid development of diagnostic technology, doctors need to process and integrate heterogeneous and complementary data. Personalized cancer diagnosis and treatment planning rely on multiple images (such as radiology, pathology, and camera images) and non-image data (such as clinical and genomic data). Through multimodal deep learning technology, researchers are committed to extracting and aggregating multimodal information to provide more objective and quantitative computer-aided clinical decision-making [24].

In clinical risk prediction, intelligent models based on the Internet of Things and electronic health record data have been established to predict complications in dialysis patients. The prediction accuracy and recall rate of these models range from 71% to 90%, indicating their potential application in clinical health services [25]. Additionally, significant progress has been made in multimodal learning methods for gastric cancer. By combining full-slice pathological images and gene expression data, prediction accuracy has been improved in multiple tasks, especially in survival prediction and pathological staging classification [26].

Prospects for Clinical Application

Multimodal data fusion technology holds vast potential for clinical applications. With the widespread use of Electronic Health Record (EHR) systems, accessing clinical data has become more convenient, providing a rich foundation for multimodal data fusion. By combining patient records from various sources, including medical tests, medical images, clinical notes, and more, researchers can more comprehensively evaluate patients' health status. This integration of multimodal data not only enhances the accuracy of clinical risk prediction but also supports personalized healthcare [27]. In terms of predicting hospital-acquired pressure ulcers, researchers have proposed an AdaBoost-based algorithm capable of detecting these ulcers even in the presence of labeling conflicts. This algorithm utilizes truth inference methods to resolve inconsistencies in labeling across different case definitions, demonstrating potential for application in clinical settings [28]. Additionally, machine learning shows promising results in predicting surgical outcomes for patients with Cushing's disease. Studies indicate that machine learning algorithms can effectively identify predictors that influence surgical results, supporting future patient care and consultation [29].

Limitations and Future Directions of Research

Despite the promising prospects of multimodal data fusion technology in clinical applications, there are still some limitations. Firstly, existing studies are often constrained by inadequate sample sizes and the accuracy of sample labeling. The lack of externally validated datasets may lead to insufficient generalization ability of the models [30]. Secondly, machine learning models may encounter overfitting or underfitting, affecting their performance on unseen data [30]. Future research directions should focus on expanding sample sizes, improving data labeling quality, and developing more robust machine learning algorithms. Additionally, optimizing and standardizing multimodal data fusion methods for different clinical scenarios will be an important topic for future studies. These efforts can further promote the application of multimodal data fusion technology in clinical decision support systems, providing patients with more precise and personalized medical services [31].

Acknowledgments

Funding

This work was supported by Science and Technology Planning Project of Guangdong Province of China (Grant number: A2023069). The authors wish to sincerely thank all of the editor teacher 's assistance in reviewing and editing this article.

Author Contributions

Study Conception and Design: XJC, SFL. **Data Collection:** PW, HLH. **Data Analysis and Interpretation:** All authors. **Drafting of the Article:** All authors. **Critical Revision of the**

Article: FQG

Ethical Approval

Ethical issues are not involved in this paper.

Conflicts of Interest

All contributing authors declare no conflicts of interest.

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