Supplementary Information

Supplementary Table 1. Typical applications and outcomes of big data in perioperative management

Data type	Application scenario	Analytical method	Key findings and clinical significance	References
Preoperative EHR	Postoperative delirium risk prediction	ML and logistic regression	The predictive performance of the ML model is significantly superior to that of traditional methods	[1]
Provincial-level medical administrative data	Prognostic prediction for emergency surgery in older adults	Comparative analysis of multiple frailty assessment models	Frailty indices significantly improve the accuracy of mortality risk prediction	[2]
Multicenter standardized EHR	Cardiac risk prediction for non-cardiac surgery	Multiple ML algorithms	ML models demonstrate significantly superior predictive performance compared to traditional scoring systems	[3]
Multi-surgery EHR	Patient risk stratification and phenotype identification	Clustering and random forest algorithms	Digital phenotyping significantly enhances postoperative risk prediction	[4]
EHR of cancer patients	Prediction of severe postoperative complications	Interpretable ML model	Accurate prediction of complications and interpretation of risk factors	[5]
Joint replacement registry and EHR data	Prediction of PJI risk	Multiple ML and traditional models	Limited improvement in model performance; clinical utility remains questionable	[6]
Preoperative electronic health record data	Postoperative in-hospital mortality risk prediction	Random forest ML	Automated risk scoring significantly outperforms traditional methods	[7]
EHR and ICD coding	Automated mortality risk scoring for pediatric surgery	Algorithmic automation and statistical comparison	Enables automated risk stratification and reduces clinical workload	[8]
Perioperative EHR	Prediction of scute kidney injury after vascular surgery	Random forest ML	Incorporating intraoperative data significantly improves predictive performance	[9]
Electronic health record data	Preoperative frailty assessment in elderly surgical patients	Comparative performance analysis of multiple frailty assessment tools	Electronic frailty tools significantly enhance risk stratification	[10]
Continuous invasive blood pressure data	Prediction of intraoperative hypotension	ML algorithm	Significantly reduces the duration and depth of hypotension	[11]
Continuous invasive arterial pressure data	Quantification of intraoperative hypotension severity	Multivariable proportional odds model	Invasive monitoring significantly improves the detection rate of hypotension	[12]
Clinical, body composition, and CT imaging data	Preoperative prediction of postoperative pancreatic fistula risk	Integration of ML and deep learning	Development of a high-precision preoperative prediction model	[13]
CT imaging and clinical data	Preoperative prediction of postoperative pancreatic fistula risk	Multivariate logistic regression	Construction of a high-accuracy predictive nomogram model	[14]
Panoramic radiograph	Prediction of third molar extraction difficulty and risk	Semantic segmentation and classification model	Construction of a high-precision preoperative decision-support system	[15]

Note: EHR, electronic health records; ML, machine learning; PJI, periprosthetic joint infection; ICD, International Classification of Diseases; CT, computed tomography.

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