Review

DOI: 10.5582/bst.2025.01047

A technological convergence in hepatobiliary oncology: Evolving roles of smart surgical systems

Xuanci Bai[1,2,§], Runze Huang[1,2,§], Qinyu Liu[1,2], Xin Jin[1,2], Lu Wang[1,2], Wei Tang[3,4], Kenji Karako[4,*], Weiping Zhu[1,2,*]

[1] Department of Hepatic Surgery, Fudan University Shanghai Cancer Center, Shanghai Medical College, Fudan University, Shanghai, China;
[2] Department of Oncology, Shanghai Medical College Fudan University, Shanghai, China;
[3] National Center for Global Health and Medicine, Japan Institute for Health Security, Tokyo, Japan.
[4] Hepato-Biliary-Pancreatic Surgery Division, Department of Surgery, Graduate School of Medicine, The University of Tokyo, Tokyo, Japan.

SUMMARY: Cancer remains a major threat to human health, with the incidence of hepatobiliary tumors consistently high. Treatment methods for hepatobiliary tumors include surgical intervention, ablation, embolization, and pharmacological treatments, with surgery being a critical component of systemic treatment for patients with hepatobiliary tumors. Compared to other methods, surgery is the most effective way to remove tumors and improve survival rates, serving as the cornerstone of various treatment strategies. However, the large patient population sometimes burdens traditional surgical oncology. In recent years, rapidly advancing artificial intelligence (AI) technologies, characterized by efficiency, precision, and personalization, align well with the treatment philosophy of oncologic surgery. Increasing studies have shown that AI-assisted surgical oncology outperforms traditional approaches in many aspects. This review, based on machine learning, neural networks, and other AI techniques, discusses the various applications of AI throughout the entire process of hepatobiliary tumor surgical treatment, including diagnostic assistance, surgical decision-making, intraoperative support, postoperative monitoring, risk assessment, and medical education. It offers new insights and directions for the integration and application of AI in oncologic surgery.

Keywords: neural networks, surgical navigation, radiomics, postoperative monitoring, medical education

1. Introduction

Despite the rapid advancement of medical technology, malignant tumors remain a major threat to life and health (*1*). Among all cancers, primary liver cancer is one of the top five most common cancers globally and the second leading cause of cancer-related deaths, imposing a heavy burden on Chinese society (*2*). Compared to liver cancer, although gallbladder cancer is less common, its five-year survival rate is lower, and it has a higher degree of malignancy. Furthermore, the liver is a common metastatic site for other cancers, and liver metastasis often indicates that the disease has reached an advanced stage, with a lower survival rate. Over time, we have witnessed changing standards of treatment for cancer, ranging from nihilism (misconceptions, poor referrals, and debulking surgeries) to realism (formal R0 resections, complex/composite resections, laparascopic resections, and robotic resections) to modern-day activism (conservative surgery, brachytherapy, and targeted therapy). Examples of the conservative trend include treatment of liver cancer, which has moved from resection to ablation (RFA, TACE, MWA, and SIRT) (*66*). Currently, multiple treatment strategies exist for liver tumors (*3*), among which surgery offers the most complete removal of tumors, significantly improving survival rates and lifespan (*4*). For biliary tumors, treatment plans must be tailored based on the patient's liver function, number of tumors, and extent of metastasis, though surgery remains the most effective approach (*5*).

However, despite surgery being an irreplaceable component in the treatment of hepatobiliary tumors, many existing issues still interfere with the efficiency and speed of the surgical process. For example, when faced with complex anatomical structures, less experienced surgeons may require more time and effort to complete tumor resections. Additionally, when cirrhosis occurs, the fragile vascular physiology imposes stricter demands on the surgeon's expertise.

With the continuous development of computer science, artificial intelligence algorithms, including neural networks and deep learning, have shown remarkable potential. In the field of oncological surgery, artificial intelligence (AI) models improve a range of processes, from preoperative assessment and intraoperative assistance to postoperative monitoring, continuously enhancing patient survival rates and quality of life, and sparking a revolution in traditional surgical models. The effectiveness of AI models is a topic of discussion, but existing studies have shown that AI-assisted surgeries, such as robotic liver resections, are comparable to traditional open liver resections in terms of treatment outcomes, while also reducing postoperative complications and improving survival rates (*6*).

2. Definition of artificial intelligence

2.1. General definitions for AI

In recent years, AI models have become increasingly prevalent in research, not only accelerating the collection, generation, transformation, and processing of data, but also assisting in experimental design and the formulation and validation of hypotheses based on experimental findings. These models have provided researchers with powerful tools, facilitating greater cross-disciplinary collaboration and integration (*7*) (Figure 1).

The field of artificial intelligence encompasses a vast range of learning algorithms, with machine learning models, particularly those based on neural networks, being among the most prominent. Commonly employed AI techniques in the healthcare domain include traditional machine learning models and deep learning models. Artificial intelligence serves as a technological nexus, bridging robotics and virtual reality with conventional surgical paradigms to facilitate their synergistic integration.

Broadly speaking, machine learning refers to the process of fitting predictive models to data or identifying patterns within data (*8*). Depending on whether the model is based on neural networks, machine learning can be classified into traditional machine learning and neural network-based machine learning. Furthermore, it can be categorized into supervised and unsupervised learning, depending on whether the training data requires classification and labeling. Traditional machine learning typically offers faster development and testing for a given problem, but often requires the dataset examples to have a consistent number of features (*8*). In practical applications, algorithms usually need to be adjusted according to the specific characteristics of the dataset, enabling faster and more accurate processing. This, in turn, increases the confidence in the derived conclusions and enhances the generalizability of the trained models (Figure 2).

2.2. Supervised learning and unsupervised learning

Supervised learning is the most commonly used form of machine learning. In supervised learning, the system is provided with features related to the learning objectives (such as patient demographics and risk factors) and the expected outcome measures (such as diagnosis or clinical events). The goal is to identify the relationship between these two elements within the dataset. When combined

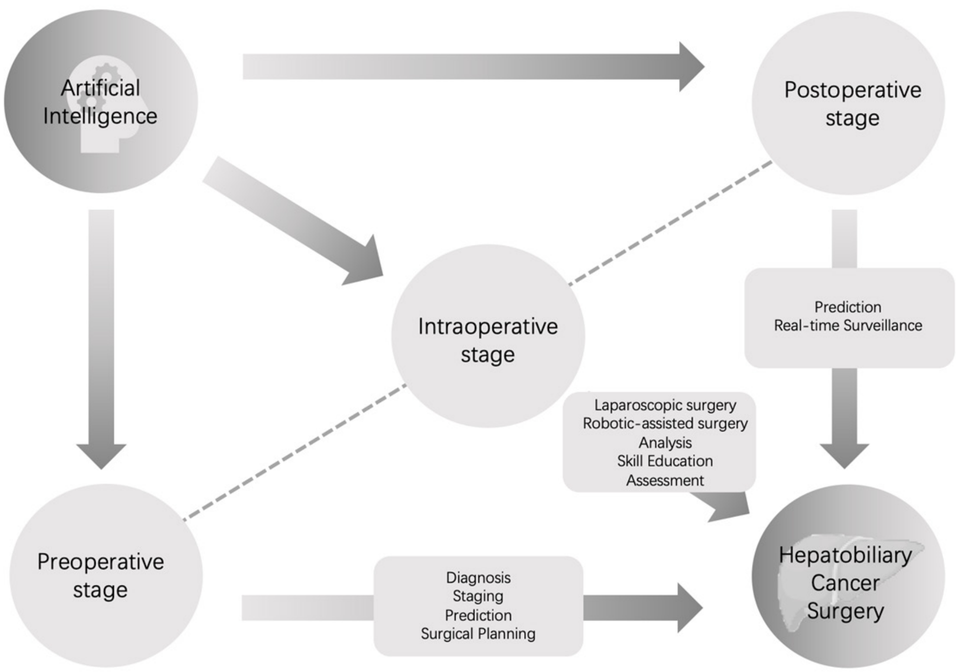

Figure 1. Integrating Artificial Intelligence Across Stages of Hepatobiliary Cancer Surgery. This figure illustrates the integration of artificial intelligence (AI) into various stages of hepatobiliary cancer surgery. AI supports the preoperative stage by enhancing diagnosis, staging, prediction, and surgical planning. During the intraoperative stage, AI facilitates laparoscopic and robotic-assisted surgeries, real-time analysis, skill education, and surgical assessment. In the postoperative stage, AI aids in prediction and real-time surveillance, ensuring better patient monitoring and outcomes.

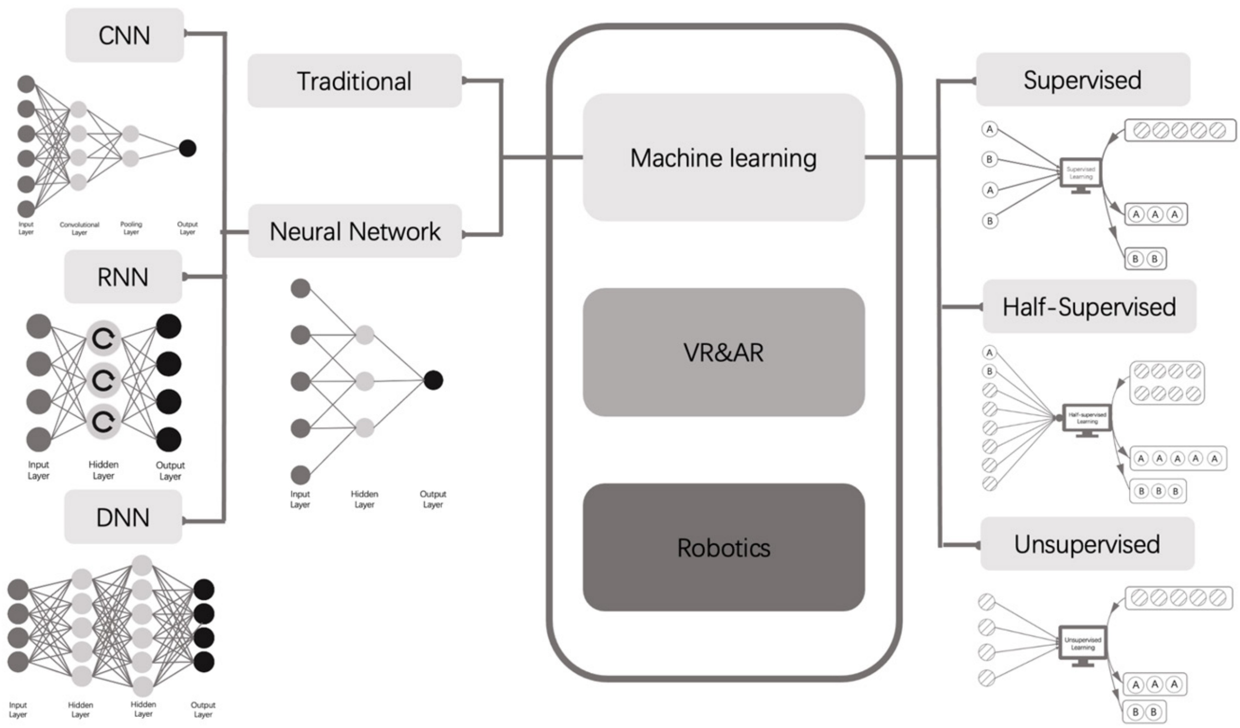

Figure 2. Framework of Machine Learning and Neural Network Applications in Medicine. This figure illustrates machine learning frameworks and neural networks in medical applications. Neural network models, including CNNs, RNNs, and DNNs, are shown on the left. The center highlights traditional and neural network-based machine learning, extending into VR, AR, and robotics. The right categorizes machine learning into supervised, semi-supervised, and unsupervised learning methods.

with other algorithms, supervised learning models can significantly enhance the speed of data processing.

In December 2023, Dong H developed a self-supervised learning model based on a sliding window (SW) approach (SWSSL) for anomaly detection in medical imaging. Validated with datasets of mammography and pneumonia X-ray images, SWSSL demonstrated its capability for specialized detection on high-resolution medical imaging datasets, helping to mitigate the problem of over-sampling in anomaly detection when relying solely on the SW method (*9*).

Beyond identifying abnormal attributes in instances, in January 2023, Tu Z and colleagues incorporated 2D image keypoints and texture from monocular video into a self-supervised learning model to achieve 3D organ reconstruction. Whether for joint movement or hand texture, self-supervised learning exhibited remarkable performance (*10*).

Unlike supervised learning, in unsupervised learning, the computer is provided with unlabeled data records (*13*), and through a self-reinforcing mechanism, it identifies and determines whether there are any underlying relationships between the input data. In other words, it learns from its own predictions and strengthens the associations between existing experiences and appropriate responses. This characteristic of unsupervised learning enables it to explore hidden relationships across multiple domains such as genomics, metabolomics, and biochemistry, providing researchers with new insights and fostering the development of interdisciplinary research directions. However, because unsupervised learning lacks associated constraints, the experiences derived from repeated self-reinforcement may not always be accurate or beneficial. The effectiveness of unsupervised learning is closely related to the consistency between the provided data characteristics and the task at hand. The higher the consistency, the stronger the effectiveness of unsupervised learning (*11*).

Similar to supervised learning, unsupervised learning can also identify abnormal structures in images by learning from normal images, enabling preoperative diagnosis and assessment of tumors. For instance, in April 2021, Baur C incorporated an unsupervised auto-learning model into the interpretation of brain MRI images, utilizing three different unsupervised auto-learning models to analyze a brain MRI dataset. Although none of the models perfectly reproduced the healthy model corresponding to the given images, the use of the unsupervised auto-learning model alleviated the need for manual segmentation of experimental data and highlighted the differences between the images in the dataset and the normal healthy model (*12*).

Beyond supervised and unsupervised learning, there exists a hybrid model that harnesses the strengths of both, known as semi-supervised learning. This approach is capable of analyzing substantial volumes of unlabeled data, concurrently leveraging a modest amount of labeled data to bolster the model's capacity for data pattern recognition. As a result, it enhances the velocity and precision of extracting insights from extensive datasets, thereby alleviating the research burden and streamlining the analytical process for scientists (*13*).

2.3. Neural network

Neural network models represent the foundational cornerstone of deep learning, encompassing a spectrum of architectures such as traditional artificial neural networks, convolutional neural networks (CNNs), deep neural networks (DNNs), and recurrent neural networks (RNNs). Notably, CNNs have demonstrated exceptional efficacy in the recent empirical literature (*14*).

The canonical structure of a convolutional neural network is comprised of alternating convolutional and pooling layers. The convolutional layers are instrumental in identifying local feature connections from preceding layers, while pooling layers aggregate semantically analogous features into singular representations. This arrangement, when stacked with fully connected layers, forms the backbone of a conventional CNN (*15*). Advanced deep convolutional neural networks have notably ameliorated the generalization weakness of their traditional counterparts, securing their status as the algorithm of choice within the domain of medical image analysis. A case in point is the research by Huang J *et al*. in 2022, wherein a CNN-based model was crafted to discern features indicative of epilepsy and schizophrenia from static and dynamic brain MRI imagery, thereby enhancing the discriminative power of the CNN-learned features (*16*). Nonetheless, deep learning models are susceptible to overfitting on training datasets, necessitating rigorous external validation to ensure their generalizability and robustness (*17*).

2.4. Artificial intelligence-enhanced robotic surgery

The field of medical robotics has become increasingly prominent within the domain of surgical procedures, with the da Vinci Surgical System exemplifying a paradigmatic application of artificial intelligence in this context. Endorsed by the U.S. Food and Drug Administration in 2005 for its utility in soft tissue surgery, this system stands unparalleled. The system operates on a master-slave remote control paradigm, where the surgeon, positioned adjacent to the patient at the master console, directs the robot (*18*). Equipped with cameras and tremor-free instruments, the robot provides the surgeon with an enhanced, magnified 3D perspective of the surgical field (*65*). The slave arm executes the surgical maneuvers on the patient, while the surgeon views the internal organs through the endoscope and adjusts the position of the slave robot by manipulating the master manipulator (*18*). The robotic surgery system boasts several key advantages, including a broader range of motion compared to laparoscopic instruments, an expanded visual field for surgery, and heightened precision in operational maneuvers.

Within the specialty of urology, robotic radical cystectomy (RARC) has reached a level of maturity. RARC is associated with reduced blood loss and transfusion rates when juxtaposed with the traditional open radical cystectomy (ORC), while maintaining superior oncological outcomes and comparable postoperative complication rates (*20*). A systematic comparison of the safety and efficacy of da Vinci robotic surgery versus conventional surgery was conducted by Liu Z *et al*. in 2017. Their findings indicated that, in the context of cervical cancer, robotic surgery outperformed both traditional open and conventional laparoscopic approaches in terms of blood loss, surgical extent, and intraoperative complications (*21*). Despite the current limitations in cost-effectiveness associated with robotic surgery, the technology is evolving, with anticipated advancements on the horizon that promise to further refine its utility and efficiency.

AI-assisted surgical interventions represent an emerging trend in the future of oncological surgery. By developing intelligent models trained on real-world surgical datasets, robotic systems can acquire capabilities to perform routine procedural tasks. For instance, a preclinical study demonstrated the feasibility of autonomous small bowel end-to-end anastomosis in porcine models under laparoscopic settings, achieving operative independence from surgeon intervention (*67*). Similar applications hold transformative potential in hepatobiliary tumor resection, such as AI-guided suction devices for intraoperative hemorrhage clearance or automated systems for superficial wound closure. By analyzing multimodal historical imaging datasets including CT and MRI scans alongside intraoperative computer vision systems for real-time image interpretation, artificial intelligence achieves automated tumor-to-healthy tissue discrimination in robotic surgery, enabling submillimeter precision during oncological resection (*70*).

2.5. Virtual reality

Virtual reality (VR) technology engenders a comprehensively immersive experience by leveraging a triad of sensory modalities: visual, auditory, and tactile. This multifaceted approach integrates real-time interactive images and sounds, simulating a spectrum of sensations akin to those encountered in the physical world, thereby harnessing the capabilities of multi-sensory technology.

Virtual reality has been extensively integrated into surgical skill acquisition, demonstrating dual transformative capacities. Primarily, machine learning frameworks incorporating clustering algorithms enable quantitative profiling of trainees' learning curves through VR-derived kinematic data analytics. By predicting proficiency attainment thresholds—quantified as required trial repetitions—these AI-powered systems assess individual competency trajectories, thereby facilitating personalized training protocols that optimize group training efficiency (*69*). Secondarily, within interactive VR surgical simulations, artificial intelligence dynamically adapts procedural pathways based on operator decisions while cross-referencing institutional databases to issue preemptive alerts regarding high-risk anatomical zones, such as error-prone dissection planes and vasculature proximity. AI-powered VR systems deliver personalized cognitive behavioral therapy (CBT) and mindfulness interventions for postoperative cancer patients, creating secure virtual environments to enhance therapeutic efficacy and improve quality of life (*68*).

In a pivotal 2019 study, Tao XM unveiled a revolutionary set of skin haptic interfaces, remarkable for their wireless control and power capabilities, eschewing the need for batteries. These innovative interfaces pave the way for augmenting VR and augmented reality (AR) experiences, transcending the traditional confines of vision and hearing (*22*). Their applications extend to material development, device design, integration strategies, and system layout. The utility of VR is already evident in various medical disciplines, including cardiac intervention (*23*), intensive care (*24*), laparoscopic surgery (*25*), and mental health (*26*). Anticipating future trends, the medical field is poised to witness an increasing integration of virtual and augmented reality technologies, heralding a new era in healthcare innovation.

3. Preoperative stage

Accurate preoperative diagnosis and assessment are critical components in the surgical management of hepatobiliary tumors. In line with clinical practice guidelines for hepatocellular carcinoma published by various countries, including China (*4*), Japan (*28*), South Korea (*29*), and the United Kingdom (*30*), definitive diagnosis of primary hepatocellular carcinoma can be established through pathology, immunohistochemistry, and radiomics. Regarding preoperative evaluation, the commonly utilized staging systems include the Barcelona Clinic Liver Cancer (BCLC) staging system (*29,30*), the modified International Union Against Cancer (mUICC) staging system (*28*), and the Chinese Liver Cancer (CNLC) staging system (*4*). These systems incorporate clinical characteristics such as tumor size and number, vascular and bile duct invasion, lymph node involvement, distant metastasis, and liver function status. Staging systems serve to aid in decision-making and prognostic assessment; thus, high-precision preoperative staging is a key determinant in the surgical treatment of hepatobiliary tumors.

Traditional preoperative risk prediction and surgical planning are subject to variations influenced by individual surgeons, potentially introducing bias. The incorporation of artificial intelligence-assisted diagnostics and staging evaluations can circumvent such variability, thereby optimizing surgical outcomes and contributing to a more standardized and refined approach to patient management.

3.1. AI-Enabled histopathology

The stratification of tumors and the assessment of microvascular invasion (MVI) are acknowledged as the two paramount prognostic indicators in the surgical management of hepatic malignancies (*31*). At present, the detection of MVI primarily relies on histopathological examination of postoperative specimens, underscoring the critical role of AI-driven models in preoperative evaluation of MVI for informed clinical decision-making. In a seminal study from 2009, Varghese *et al*. harnessed preoperative variables, including tumor volume, to train an Artificial Neural Network (ANN), revealing that the ANN outperformed conventional linear predictive models in accurately discerning Hepatocellular Carcinoma (HCC) grade and MVI status (*32*). Advancing this field, in 2020, Saillard *et al*. employed a pre-trained Convolutional Neural Network (CNN) to analyze HCC histopathological images, extracting features that were subsequently utilized to develop two distinct deep learning algorithms for the prediction of patient survival rates. These models demonstrated superior predictive accuracy over composite scoring systems in estimating survival rates for liver cancer, thereby validating the integrative application of AI algorithms in the preoperative prognostic assessment of HCC patients (*27*). Furthermore, the identification of specific immunogenic genes within histopathological images has been instrumental in shaping preoperative strategies. Illustratively, in 2022, Zeng *et al*. from France developed a suite of deep learning models, including Patch, Multiple Instance Learning (MIL), and Clustering Constrained Attention Multiple Instance Learning (CLAM), for the analysis of histological images. Notably, the CLAM model excelled in screening efficacy, showing promise in predicting patient responsiveness to immunotherapeutic interventions (*17*).

3.2. AI-radiomics

Integrating AI with hepatobiliary oncologic radiomics for enhanced preoperative diagnostics, surgical planning, and prognostic assessment: Mazzaferro V *et al*. in 2008 established that microvascular invasion, irrespective of its size or quantity, is a significant predictor of poorer overall survival and increased post-transplant recurrence in hepatocellular carcinoma patients undergoing liver transplantation, marking it as the most influential covariate impacting patient prognosis (*34*). Current preoperative assessments are limited to providing pre-emptive probabilities of MVI or associated biomarkers (*34*). The deployment of AI models allows for a more nuanced prediction of MVI extent and a more accurate prognostic determination. A case in point is the work by Xia TY in 2023, who pioneered a radiomics methodology predicated on preoperative multiphase CT scans to prognosticate MVI, utilizing hybrid models to forecast MVI status and, consequently, patient recurrence survival rates (*33*).

Expanding beyond MVI, the evaluation of donor liver volume and vascular architecture is pivotal to the safety and postoperative survival rates associated with liver transplantation. Conventionally, the preoperative phase of living donor liver transplantation necessitates manual segmentation of the resection plane by surgeons based on CTA imaging of hepatic vasculature (*37*). This process is not only labor-intensive but also susceptible to inaccuracies due to the partial volume effect, which can obscure tumor margins. The incorporation of artificial intelligence significantly bolsters the reproducibility of tumor segmentation (*36*). Illustratively, between 2022 and 2023, Oh N developed a residual model based on pre-transplant CTA data, facilitating the construction of a 3D liver model. This model enabled automated segmentation of liver parenchyma and vascular structures, as well as volumetric assessment derived from these segmentations. When compared to manual surgical segmentation, artificial intelligence yielded more consistent and stable outcomes, demonstrating a higher correlation with actual values (*37*).

Although PET-CT possesses significant diagnostic and evaluative utility, its broader implementation is hindered by inherent limitations, such as fusion artifacts and motion-related image degradation. The deployment of artificial intelligence technologies offers a means to mitigate these issues by reducing image noise and augmenting image quality. Consequently, AI enhances the accuracy of preoperative diagnostic procedures, tumor staging, therapeutic decision-making, and the assessment of treatment responses (*38*).

In the context of metastatic liver cancer, artificial intelligence holds substantial promise. For instance, in the case of colorectal cancer, preoperative identification of high-risk patients with a poor prognosis is crucial to avoid unnecessary aggressive treatment. A pertinent example is the work by Keyl J *et al*. in 2022, who utilized a pre-trained convolutional neural network-based nnU-Net model to extract prognostic parameters from abdominal CT images of patients with colorectal liver metastases. This included the automatic segmentation of metastatic liver lesions, leading to the development of a personalized survival risk prediction model for advanced-stage colorectal cancer patients (*39*).

Furthermore, additional clinical indicators significantly influence the preoperative risk assessment of hepatobiliary tumors. In 2024, Jin Y *et al*. introduced a suite of five machine learning-based models, encompassing Logistic Regression (LR), Random Forest, Extreme Gradient Boosting (XGB), Light Gradient Boosting Machine (LGBM), and Artificial Neural Networks. These models were employed to assess various patient examination indicators, with the ANN model demonstrating superior performance. It was capable of early identification of patients at an elevated risk of Posthepatectomy Liver Failure (PHLF) (*35*).

4. Intraoperative stage

Within the realm of surgical interventions, the caliber of the surgeon's technical skills often surpasses perioperative care in its impact on surgical outcomes. Proficiency in surgical techniques is paramount for the prevention of intraoperative complications such as hemorrhage or vascular occlusion and may correlate with reduced procedural durations, consequently mitigating the risk of postoperative morbidity (*40*).

4.1. Artificial intelligence-enhanced laparoscopic surgery

Laparoscopic surgery has become widely recognized for its merits. When juxtaposed with open surgical approaches, laparoscopy is associated with more favorable rates of perioperative and postoperative complications, as well as abbreviated hospitalization periods (*41*). However, as the indications for laparoscopy broaden, several challenges have come to light. Notably, the intricate anatomical structures and vascular networks encircling the liver necessitate meticulous identification and circumvention during laparoscopic procedures. Furthermore, the insufflation of gas for pneumoperitoneum can induce liver displacement, distortion, and torsion of the hepatic hilum vessels (*19*), creating disparities between preoperative radiographic images and intraoperative realities, which augments the complexity of the surgery (*42*).

Incorporating artificial intelligence technologies such as Virtual Reality and Deep Learning (DL) in laparoscopic hepatectomy is considered to mitigate the aforementioned challenges to a significant extent. DL can be utilized to identify anatomical structures within the surgical field, thereby reducing the risk of adverse events. In 2020, Madani A *et al*. trained a pyramid scene parsing network model, composed of a convolutional neural network and a multi-scale pyramid pooling module, using several frames from laparoscopic cholecystectomy videos. The results demonstrated that this model could efficiently recognize key structures in the surgical area during laparoscopic cholecystectomy (LC) (*43*).

The integration of VR with surgical procedures has emerged as a hot topic in recent research. In 2022, Ramalhinho J interactively superimposed a 3D model of the liver, including the liver surface, vasculature, and virtual target tumors, onto laparoscopic liver views. Three methods were compared for participant tumor localization accuracy: unguided, single-screen display, and augmented reality overlay. The conclusion was that any form of guided display improved performance and usability compared to unguided surgery, with the single-screen display showing the most significant results. However, participants expressed a preference for AR overlay that enhanced precision, which in turn augmented the performance and decision-making capabilities during laparoscopic surgery (*44*).

4.2. Robotic-assisted surgery

The field of robotic surgery has witnessed remarkable progress in recent years, with substantial evidence supporting the safety and efficacy of robotic hepatectomy as a viable alternative to laparoscopic hepatectomy. A study conducted by Jeong IG in 2017 indicated that robotic-assisted nephrectomy does not confer an increased risk of major complications when compared with laparoscopic approaches (*45*). Furthermore, a multicenter randomized controlled trial by Feng Q *et al*. in 2022 demonstrated that, for patients with mid to low rectal cancer, robotic surgery offers superior tumor resection, reduced surgical trauma, and enhanced postoperative recovery over conventional laparoscopic surgery (*46*). In 2024, Birgin E conducted a single-center randomized controlled single-blind study on patients with resectable liver malignancies, revealing no significant disparities in quality of life, perioperative morbidity, or oncological outcomes between those who underwent robotic hepatectomy and those who underwent laparoscopic hepatectomy (*47*).

In liver transplantation, the utilization of robotic systems is in its nascent stages. In April 2022, South Korea executed a pioneering procedure involving laparoscopic donor and recipient hepatectomy followed by robotic-assisted living donor liver transplantation. The robotic surgery system's advantages include stable visualization, facilitation of microsurgery, and incorporation of tremor correction and articular motion functionalities (*48*). In August 2023, Saudi Arabia marked a milestone by performing the world's first fully robotic living donor hepatectomy and liver transplantation implantation using the da Vinci Surgical System. This approach, in comparison to traditional hepatectomy, offers a three-dimensional perspective of the surgical field, enhanced visualization, and refined manipulation capabilities (*49*).

Despite the demonstrated precision, efficacy, and safety of robotic surgery systems in hepatobiliary tumor surgery, several challenges persist, including the constraints of limited operating space, restricted visual fields, difficulties in hepatic venous anastomosis due to excessive tension, and the high skill requirements for surgeons.

4.3. Artificial intelligence in the analysis of laparoscopic videos

The observation of surgical procedures is a rich educational resource for resident surgeons. A cardinal principle in medical education, particularly when acquiring new operative techniques, is encapsulated by the adage 'see one, do one, teach one'(*50*). By observing hepatobiliary surgical procedures, novice learners can closely scrutinize the intricacies of the operative process, thereby gaining a more profound comprehension of the anatomy and vascular architecture of abdominal organs such as the liver, as well as becoming intimately acquainted with the diseases under study and the procedural steps involved.

Laparoscopic surgery is particularly amenable to the development of audio-visual educational materials, with surgical videos providing an accurate depiction of the surgeon's viewpoint, thereby offering students essential insights into anatomical structures and the sequential steps of surgery (*51*). The task of manually indexing and analyzing these surgical videos is arduous and resource-intensive; thus, the employment of artificial intelligence for automated video indexing and as an adjunct in surgical pedagogy is not only warranted but also offers significant pedagogical benefits.

The task of automatically discerning surgical phases from video footage alone is inherently challenging. Initially, there is a paucity of inter-class distinctions between various phases, while substantial intra-class differences exist within the same phase. Additionally, the scene's clarity is often compromised due to factors such as camera movement and surgical smoke, which exacerbate the complexity of phase identification. Thirdly, the camera may not persistently capture the surgical field during intricate procedures, introducing extraneous imagery into the video record (*52*). Therefore, to attain a high degree of accuracy in the automated segmentation of surgical phases, it is essential to develop a model capable of concurrently harnessing video imagery characteristics, kinetic features, and spatiotemporal attributes.

Among the myriad of artificial intelligence algorithms, convolutional neural networks (CNNs) hold a distinct advantage in image and object recognition, frequently being employed to identify intraoperative characteristics in surgical videos, such as insufflation pressure and operating table position, tool usage and application—including the timestamps for the deployment and cessation of each instrument, as well as their usage patterns—video feature extraction and learning, such as operation recognition, and the prediction of remaining surgery time, thereby enhancing the efficiency of video review (*53*). In July 2016, a study from France introduced a novel CNN framework named EndoNet, designed for detection tasks like tool presence and phase identification, while also analyzing the impact of the volume of training data on the framework's performance. This addressed phase identification issues in laparoscopic surgery and pioneered a new method for directly learning visual features from raw images (*54*). In May 2018, researchers from Hong Kong presented an innovative approach to surgical video analysis by integrating deep residual networks (ResNet) and long short-term memory networks (LSTM) to construct a novel recurrent convolutional neural network framework, SV-RCNet. This framework extracts visual features and temporal models from videos and is trained to recognize discriminative features in surgical videos, thereby accurately identifying surgical procedural steps (*52*). In March 2020, a study from Japan utilized a CNN model capable of identifying specific segments of laparoscopic surgery, assigning video clips to predefined surgical phases based on their characteristics, and constructed a large annotated surgical video dataset. Training CNNs requires a substantial amount of labeled data and significant parallel computing power, making this research conducive to the refinement of CNN models with potential applications in automated video indexing and surgical skill assessment (*55*).

Artificial intelligence is increasingly being employed for the identification of fundamental motion characteristics within surgical video contexts, particularly for simple procedural actions such as suturing, needle passing, and knot tying that are common in robotic minimally invasive surgery. The categorization of surgical gestures from video data is facilitated through the application of Linear Dynamical Systems (LDS), Bag of Features (BoF) models, and a synergistic approach combining both methods within a Multiple Kernel Learning (MKL) framework. These methodologies have been instrumental in the development of an integrated framework that amalgamates video and kinematic data, thereby enhancing the accuracy of surgical gesture recognition. This advanced capability not only aids in the execution of rudimentary surgical maneuvers and provides real-time feedback on procedural deficiencies, which can lead to reduced operative times and diminished surgical risks, but also serves to activate context-sensitive information displays. Specifically, when an AI model identifies a particular gesture, it can anticipate the forthcoming actions required by the surgeon and the tools that may be necessary, thus enabling the surgical team to proactively prepare for imminent procedural steps (*56*).

4.4. Artificial intelligence in surgical skill education

Within the paradigm of Robotic-Assisted Surgery (RAS), the conventional pedagogical approach of 'see one, do one, teach one' (*50*) has reached its limitations. The adoption of Virtual Reality models for the simulation of RAS procedures represents a more efficacious avenue for novice surgeons to acquire and refine their technical skills. While research has yet to fully substantiate the effectiveness of VR in mastering the intricacies of robotic surgery, the anticipated enhancements in VR model precision are poised to markedly transform the landscape of surgical training (*57*). In 2018, a forward-looking randomized controlled trial in the United Kingdom assessed the comparative efficacy of 2D video and 360-degree VR video in teaching single-handed surgical knotting. The study revealed that the immersive 360-degree VR video significantly outperformed the 2D modality in knotting skill acquisition, underscoring its potential as an educational tool (*58*).

4.5. Application of artificial intelligence in the video-assessment of surgical skills

The American Board of Surgery (ABS) recognized in 2023 the utility of Video-Based Assessment (VBA) as a complementary tool for evaluating the technical proficiency of surgeons, affirming its role in identifying and providing corrective feedback to underperforming surgical candidates (*59*). Machine learning techniques offer the promise of streamlining VBA processes, thereby augmenting the efficacy of skill evaluation. Nonetheless, the deployment of unsupervised deep learning models can engender what is often referred to as the 'black box' phenomenon, which obscures the rationale behind the scoring, thus impeding the ability of the assessed to discern the factors contributing to their performance outcomes (*60*).

5. Postoperative stage

5.1. Artificial intelligence for postoperative morbidity and survival prediction

Deficiencies in postoperative surveillance can result in the misclassification of patients at elevated risk for complications, potentially leading to their placement in general wards rather than intensive care units. In 2021, Loftus TJ utilized established random forest and nearest neighbor algorithms to demonstrate that inadequate triage is associated with increased mortality and morbidity rates (*61*). The principal aim of AI in the postoperative period is to prognosticate the likelihood of postoperative complications, promptly detect suboptimal triage scenarios, and facilitate real-time patient monitoring. The MySurgeryRisk AI system, which integrates electronic health record (EHR) data with machine learning algorithms—including generalized additive models and random forests—predicts postoperative complications with increasing accuracy as more features are incorporated into the model (*62*). In June 2021, Bonde A conducted a retrospective analysis, training a deep neural network (DNN)-based postoperative risk prediction model within a structured electronic medical data system. This analysis revealed that the model's performance escalated with an increased number of input variables, and even in the presence of incomplete data, the DNN model retained a high degree of precision.

This suggests that the integration of AI has transformed postoperative complications from an enigmatic risk into a foreseeable and manageable one (*63*).

For the majority of neoplasms, postoperative pathological imagery is intricately linked to patient prognosis. The deployment of convolutional neural network models on whole-slide imaging (WSI) of digital histological sections from patients who have undergone hepatectomy for hepatocellular carcinoma enables the generation of risk scores. These models can autonomously pinpoint the most pertinent risk areas within WSI, thereby facilitating the prediction of post-hepatectomy survival. Their predictive accuracy surpasses that of traditional prognostic models that combine clinical, biological and pathological characteristics. Nonetheless, there is a dearth of research attesting to the robust generalizability of these models (*27*).

5.2. AI-based real-time postoperative surveillance

AI-based real-time postoperative surveillance holds a distinct advantage in its capacity to merge instantaneous predictive analytics with clinical and digital workflows. The transformative potential of AI in enhancing patient survival rates following surgery is most notably realized through its capability to identify shifts in patient clinical trajectories in a timely manner. This facilitates a smooth transition between in-hospital and remote monitoring, such as through smartwatch-integrated remote electrocardiogram monitoring. Such technology encourages prompt medical engagement among postoperative patients, thereby reducing postoperative morbidity rates (*64*). This strategy not only bolsters patient outcomes but also optimizes the allocation of healthcare resources, contributing to a more efficient and sustainable healthcare delivery model.

6. Conclusion

In recent years, hepatobiliary tumors have persistently posed a significant threat to human health. The convergence of AI models, including neural networks, deep learning, robotic technology, and virtual reality, with surgical treatments for hepatobiliary tumors has the potential to yield a synergistic effect that surpasses the sum of its individual components. This integration aims to achieve the dual goals of reducing incidence and mortality rates, while simultaneously improving survival rates and prolonging survival times. Although AI faces a myriad of challenges in practical application, such as issues of medical ethics and morality, the need for clinical standardization, and concerns regarding model generalizability, the ongoing refinement and training of AI technologies are poised to exert a profound influence on the paradigms of hepatobiliary tumor surgery.

Funding: This work was supported by National Natural Science Foundation of China (81874056,81874182), the National Key Research and Development Plan of the Ministry of Science and Technology (2022YFE0125300), the Shanghai Natural Science Foundation Project (22ZR1413300), and the Public Health Bureau Foundation of Shanghai (202240240, 201940043).

Conflict of Interest: The authors have no conflicts of interest to disclose.

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Received July 3, 2025; Revised July 29, 2025; Accepted August 2, 2025.

[§]These authors contributed equally to this work.
**Address correspondence to:*
Kenji Karako, Hepato-Biliary-Pancreatic Surgery Division, Department of Surgery, Graduate School of Medicine, The University of Tokyo, Tokyo 113-8655, Japan.
E-mail: tri.leafs@gmail.com

Weiping Zhu, Department of Hepatic Surgery, Fudan University Shanghai Cancer Center, Shanghai Medical College, Fudan University, Shanghai, 200032, China.
E-mail: wpzhush@hotmail.com

Released online in J-STAGE as advance publication August 4, 2025.