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FROM TUMOR RESECTION TO PROGNOSIS: THE ROLE OF AI IN FORECASTING RECURRENCE AND SURVIVAL IN SURGICAL ONCOLOGY

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ABSTRACT

Surgical resection of solid tumors still is the first choice in curative treatment. Up to now, large part of patients have been suffered from postoperative recurrence which largely decrease long survival or affects life quality. Current prognostic strategies (mostly TNM staging and clinicopathological features) provide low accuracy because they do not reflect the biology complexity and diversity of tumor progression. Artificial intelligence is a breakthrough technology that can improve prediction of recurrence and survival for surgical oncology by evaluating sophisticated analyses of high-dimensional, multimodal data.

This narrative review provides an overview of the emerging role of AI-based prognostication after tumor resection in common types of cancer, such as colorectal, lung, breast cancer and hepatobiliary, gastroesophageal and other solid tumors. ML, following the tool provided by DL and integrative multi-omics, can achieve higher prediction performance in contrast to conventional prognostic systems through revealing nonlinear knowledge based on radiological imaging, digital pathology images, genomic characteristics as well as clinical sources. There is promising potential for AI- based tools to inform individualized surveillance intervals, adjuvant therapy decision-making, consistent patient involvement in shared decision making and re-purposing healthcare resources at the time of treatment.

Despite the promising progress, challenges remain, such as data silos, lack of generalizability raised by available models interpretability issues, workflow integration difficulties and evolving ethical and regulatory frameworks. Emerging areas—explainable AI, federated learning, multimodal data integration and real-

time intraoperative risk appraisal—will likely advance clinical translation and supporting precision-guided postoperative care. Under the current evidence of AI-based prognostic tools, this review identified promising and constraints on both aspects: interdisciplinary efforts are warranted to ensure competent, safe and equitable integration into surgical oncology practice.

INTRODUCTION

Surgery is still the mainstay of curative treatment in solid tumours. Despite the improvement in surgical approaches, perioperative management and multimodal oncologic treatment regimen which have been well established, some patients still develop disease recurrence (1,2). Reported varying recurrence incidence rate in various stages and types of cancer such as 30–50% in colorectal cancer, up to 20–30% in breast cancer and over 70% in advanced pancreatic cancer (3–7). The recurrence may occur locally, regionally or as distant metastases, which largely affect the survival and life quality of patient (8). Thus, early identification of patients at high risk of relapse is necessary to dictate the choice of adjuvant treatments, clinical monitoring and appropriate intervention (9). Nonetheless, the prediction of which patients would relapse is still a major clinical problem (10).

Clinical and pathological parameters—such as tumour size, nodal involvement, histological grade, margin status -and molecular biomarkers continue to be the standard of care for prognostic assessment in surgical oncology (11). Of these, the Tumor–Node–Metastasis (TNM) staging system is most commonly used (12). Although the TNM classification has standardized patient stratification, it oversimplifies tumor biology and neglects the complex interplay of micro-environmental and molecular factors that are responsible for the progression of a malignant disease (13–15). Patients at the same stage also often have very different outcomes indicating that staging alone is insufficient (16). These classic models, even adding further variables as lympho-vascular invasion or genomic profiling techniques or serum tumor markers generate risk estimates with low precision and unsatisfactory generalization (7,17,18). The sparse input output data integration also reflects poor generalization capacity, and usage of static models which do not consider dynamic longitudinal clinical information encumber practical use (3,19). Accordingly, there is a need for newer functionalities to make use of high-dimensional multimodal data together to deliver personalized graphs based on recurrence and survival (18).

Artificial intelligence (AI), including machine learning (ML) and deep learning (DL), has recently become a transformational technology in cancer (20). By being able to work with large, heterogeneous datasets like radiologic imaging, pathology slides, genomics and proteomics data, or electronic health records systems, for example — AI can pick up on complex non-linear patterns these data may contain that go unseen in traditional statistical approaches (21–23). AI models in surgical oncology Surgical oncology has brought the early promise of AI-based models, including resection recurrence prediction, disease-free survival, overall survival and response prediction (24,25). For example, histopathology images and DL algorithms can detect subtle morphological features associated with tumor aggressiveness, while ML models trained on radiomics features can stratify patients beyond what is possible by using conventional staging systems (26,27). Integrating multi-omics data further improves prognostic accuracy by taking tumor biology and host immune response into account. Such capabilities make AI a promising complementary test to the standard of care, which may ultimately allow for individualized risk predictive and

surveillance strategies following tumor resection (28).

The current narrative review plans to assess the growing status of AI in predicting recurrence and survival after resection therapy of patients with cancer. We review the ongoing state of AI-based prognostication tools in these common cancer types, outlining methods and data source—imaging, pathology/cytology, clinical metadata and molecular information. We evaluate the AI models against traditional prognostic systems to determine their real-world clinical value. Finally, open issues on aspects related to the development of models are discussed in terms of validation, interpretability, clinic practice assimilation (utility), and ethical and regulatory implications. We conclude by considering directions for the future, via such methods as multimodal fusion approaches, federated learning frameworks and means to improve both generalizability and equity in AI-based prognostication. Through summarizing current knowledge, the work seeks to provide a better understanding of the potential and boundaries of AI in surgical oncology and proposes directions for future studies to advance personalized postoperative care.

AI Methodologies in Prognostication

Machine Learning Approaches

ML is a family of computational algorithms that are applied to analyze clinical data and create predictive models, including but not limited to a number of algorithm methods implemented in the current study (29). Classical ML methods, such as logistic regression, support vector machines (SVMs), random forests (RF), and gradient boosting machine (GBM) and k-nearest neighbors (k-NN) have been widely used in the field of surgical oncology for predicting recurrence risk and survival after tumor resection (30,31). These models are based on clinicopathological factors including Tumor-stage, grade, margin of resection, patient demographics and laboratory information and treatment details to stratify patients into prognostic groups (10). Ensemble methods such as RF and GBM have been proven as strong performers compared to other techniques because they combine multiple learners, prevent overfitting and handle nonlinear interaction effects (26). The advent of ML-driven radiomics has also introduced a new dimension of prognostication by identifying quantitative high-value features within different imaging modalities (CT, MRI, PET) that are beyond human visual perception and can capture tumor heterogeneity and microenvironmental aspects (32,33). Model interpretability is also a notable feature of many ML methods, in particular tree-based models and regularized regression, which enables clinicians to consider variable importance and decision paths (34). But the performance of model depends on data quality, if feature engineering effectively and if we are approaching complex tumour biology. Moreover, as data become more organized and high dimensional, ML methods remain essential for creating clinically actionable prognostic profiles (8).

Deep Learning and Neural Networks

Deep learning (DL) is a branch of AI, which consists on multi-layered neural networks offering distinct efficiencies in the processing of massive and complex data (35). Due to its learning hierarchy structure, it automatically extracts discriminative features without manual engineering and is particularly effective when applied to image based and high-dimentional data (36). In surgical oncology, convolutional neural networks (CNNs) have revolutionized the analysis on histopathology slides, radiological images and intraoperative imaging (23,34). These models are able to detect subtle morphologic patterns, tumor–stroma interactions, lymphovascular invasion, and microenvironmental signatures predictive of recurrence and/or survival (37). Similarly,

recurrent neural networks (RNN) - based models and transformer-based architectures can leverage longitudinal clinical data for dynamically modeling postoperative risk trajectories (38). Existing DL methods also perform better than typical ML benchmarks, on both raw imaging and genomic data. The relationships are complex and nonlinear and consistent with biology leading to more individualized prognostication (39). But both are also "black box" systems that require significant computing power, big annotated databases and ability to generalize, thus tempering their widespread clinical use (40,41). There continue to be efforts in model explainability, federated learning and domain adaptation that aim to address these challenges.

Multi-Omics Integration

The prognosis of cancer is naturally reliant upon an array of biological features ranging from genomics, transcriptome, epigenome to proteome/metabolome and the tumor microenvironment (21,42). Integration of multi-omics profiles further enables indepth description of these layers, including capturing molecular drivers of recurrence and survival (42). ML and DL algorithms incorporated in AI-focused multi-omics arrangements fuse different types of data into cohesive prognostic systems (43). Integrative strategies have been used to determine molecular signatures that predict relapse after surgical resection of tumors, especially in breast, colorectal, lung and hepato-cellular carcinomas (38,44). In many cases, Graph-based neural networks methods, autoencoders (AE) and ensemble models have been shown to effectively capture latent features from cross-platform data (28,43). Because of the reflection of tumor evolution and anti-tumor immune activity, multi-omics models can brim with sensitivity and specificity compared to single-modality predictors (43). Incorporation of imaging or clinical metadata (radiogenomics/pathogenomics) enhances prediction granularity, allowing precise risk stratification. However, the lack of sufficiently large harmonized multimodal sources of big data, technical issues concerning multimodality integration and onerous computational requirements are still significant hindrances (24,45).

Strengths and Weaknesses of Each Method

Approach	Strengths	Weaknesses
Machine Learning	Works well with structured clinical/clinicopathological data Often interpretable, especially linear or tree-based models Requires relatively smaller datasets Efficient and computationally inexpensive	Limited ability to capture complex tumor biology Requires manual feature selection/engineering Performance decreases with highly unstructured or high-dimensional data
Deep Learning / Neural Networks	Automatically extracts high-order features Excellent for imaging, histology, and genomics Can model nonlinear, complex patterns Demonstrates superior predictive accuracy in many cases	Requires large labeled datasets Often opaque/"black box" models Computationally intensive Potential for overfitting and poor generalizability
Multi-Omics Integration	Provides holistic biological characterization Enhances recurrence and survival prediction Captures tumor evolution and immune response Enables true precision prognostication	Requires harmonized multimodal datasets Data scarcity and cost barriers Complex normalization and integration pipelines Difficult to interpret and validate clinically

Overall, AI-based prognostic methodologies are evolving rapidly, with each offering unique advantages. Classical ML provides interpretability and practicality, DL offers superior pattern recognition in high-dimensional data, and multi-omics integration promises the most biologically comprehensive predictions (35). Combining these approaches may ultimately yield the most robust prognostic models for guiding personalized postsurgical oncology care.

Applications of AI in Surgical Oncology

Colorectal Cancer

Anatomically, the colorectal cancer has been one of the most well-investigated cancer sites for AI-based prognostication because there is a rich availability of digital content such as imaging data, digital pathology images metadata and genomics (22,46). Recurrent disease is a concern following surgical resection and occurs in nearly one-third of patients (3). Both ML and radiomics models using pre- or postoperative CT or MRI have shown robust prediction ability for recurrence and disease-free survival by reflecting intratumoral heterogeneity and micro environmental patterns (19,47). Whole-slide histopathology image analysis using deep learning (DL) methods has been applied to identify high-risk features such as TB and stromal signatures, which might be challenging for a pathologist to identify (39,48). Integrative omics-AI models have been also promising in stratifying patients according to genomic instability, immune infiltration and transcriptomic signatures for the purpose of predicting relapse, response to adjuvant chemotherapy (21). These instruments offer opportunities for personalized surveillance and therapy planning beyond traditional TNM classification.

Lung Cancer

The prognosis of lung cancer after surgical resection varies greatly during the same TNM stage, indicating that more effective techniques are required. AI models integrating radiomics features extracted from CT scans can detect subtle imaging patterns, including texture and intensity changes that are associated with microscopic residual disease (RSerial) and metastatic potential (9,49). Deep learning-based models have also been trained to analyze histologic slides for identifying distinguishing features among patients with early recurrence and long-term survival (44). Furthermore, hybrid models combining clinicopathological features with radiogenomic signatures have demonstrated superior performance compared to conventional risk stratification approaches for disease-free survival and overall survival (9,44). Such developments might help to inform postoperative management, such as recognition of high-risk patients who could derive benefit from adjuvant chemotherapy or enhanced surveillance (9,44).

Breast Cancer

Breast cancer is a highly heterogenous disease, with different outcomes with respect to both surgery and systemic treatments (9). AI applications are being developed for making recurrence/metastasis/survival predictions applying multimodal (imaging, histopathologic genomic profiling) data (25). Deep learning applied to histopathology has revealed microarchitectural features and tumor-immune interactions that are independently associated with relapse (50). ML models based on gene expression signatures long used in the clinic—for example, related to HR status and proliferative pathways—improved predictive accuracy relative to commercial assays (31,51). Further, radiomics analysis of mammography, ultrasound (US) and MRI have also enhanced risk prediction by quantifying subvisual phenotypic features of recurrence (52,53). These models have potential to guide the intensity of adjuvant treatment and follow-up.

Hepatobiliary Cancers (Liver, Pancreas)

Hepatobiliary neoplasms, such as hepatocellular carcinoma (HCC) and pancreatic ductal adenocarcinoma (PDAC), often present with high rates of post-resectional recurrence; these may exceed 60–70% (48,54,55). Using AI-related prognostic models, CT- and MRI-based radiomics signatures could predict MVI, tumor aggressiveness, as well as postoperative recurrence (56,57). In HCC, DL-driven pathology and multi-omics integration (transcriptomics, methylation and proteomics), have enabled better identification of patients who are candidates for early recurrence, potentially influencing the use of adjuvant therapy or eligibility for liver transplantation (57). Parallel radiogenomic models in PDAC have also discovered biologic properties associate with chemoresistant and poor survival. In hepatobiliary malignancies, AI-based approaches are particularly relevant as traditional prognostic tools are oftentimes inaccurate and therapeutic options for patients are few (28,34,58).

Gastroesophageal Cancers

Gastric and esophageal cancer have a high risk of recurrence after curative resection(59,60). Prognostic models using AI Analysis of pre- and postoperative CT imaging, endoscopic findings and histopathology have been developed (32). Radiomics models can predict imaging features related to lymph node metastasis, tumor depth of invasion and stromal characteristics (61). On the other hand, DL methods for histopathology slides have discovered cellular phenotypes that are predictive of aggressive behavior (62). Certain integrative models based on imaging, pathology, and genomic profiles have even performed better than traditional staging systems for survival prediction. These tools could potentially be useful for risk-adapted postoperative therapy and shorter surveillance intervals (50).

Solid Tumors (Various Except Prostate, Sarcomas, and Gynecological)

Applications of AI in the other solid tumors, such as prostate cancer, bone-tissue sarcomas and gynecological neoplasms are also emerging but less developed than common cancers (39,63,64). In the context of prostate cancer, ML models with pathology, MRI-radiomics and genomic risk scores have improved the prediction of biochemical-recurrence following radical prostatectomy (63). DL-enhanced histopathology has the potential to identify aggressive tumor phenotypes and direct post-operative care (50). Due to their low incidence and heterogeneity, sarcomas are associated with specific challenges, but AI and radiomics have started to demonstrate the ability of predicting local recurrence, metastatic patterns and even overall survival after surgery (65,66). Gynecologic malignancy such as ovarian and endometrial tumors have prompted more recent multi-omics-AI tactics using radiogenomics and immune scores to predict recurrence which may impact the role of adjuvant chemotherapy or maintenance therapy (67,68). As a whole, AI has demonstrated remarkable potential in various types of cancers for predicting recurrence and survival following resection. Although the strength of evidence varies from tumor to tumor, a uniform trend reflects the transformative role AI-based models can take in fine-tuning individual prognostication and personalized postoperative care pathways (24,44,49,69,70).

Clinical Implications

Personalizing Surveillance Schedules

Oncologic postoperative follow-up is conventionally divided into organized check-ups according to tumour type, stage and guidelines (14). Yet these population-based regimens do not take into consideration variations in the likelihood of recurrence at

an individual level, and risk under-probing high-risk individuals or over-imaging low-risk populations (71). AI-based prognostic models provide personalized follow-up routes, through integrating multimodal data including imaging, histopathology, molecular signatures and clinical variables to predict probabilities of recurrence for each patient (22,43,71,72). For instance, AI technologies may be able to estimate if recurrence is more likely earlier or later and the imaging schedule that should be followed (32,69,73). This risk-adapted approach to monitoring may allow earlier detection of relapse when first-line interventions are more likely to be effective and spare patients at lower risk from the burden of overtesting thereby improving quality of life and decreasing emotional distress.

Guiding Adjuvant Therapy Choices

One of the main potential benefits of AI-based prognostication is its role in deciding about adjuvant treatment (55,74,75). The currently used clinicopathologic features and stage-specific guidelines with limited biomarker incorporation generally dictate if adjuvant chemotherapy, radiation, immunotherapy or targeted agents should be administered (55,75). But patients with the same staging can face very different outcomes, illustrating shortcomings of standard measures. AI models can predict the actual high risk patients that will have significant benefit from other therapy after surgery, even if they are not indicated by standard markers of risk (8,69,73). Conversely, women with a predicted low risk of recurrence can safely be spared the toxicities and costs of adjuvant therapy (39,75). Multi-omics AI models can also predict response to therapy and help guide clinicians who must pick the most effective regimen; for example, identifying patients likely to respond to immunotherapy using signatures from the tumor immune microenvironment. In the long run, AI-influenced decision making could lead to better survival without overtreatment (29,76).

Improvements in Shared Decision-Making and Patient Counseling

Accurate prognostic prediction is crucial for shared decision-making, where patients and clinicians must clearly consider treatment options and future hopes (77). Artificial intelligence (AI)-based models that estimate personalized survival and recurrence can support conversations on risk, benefits and patient preferences (63,78). Having the capability to see risk factors, or provide explanations in the form of drivers of a patient's predicted prognosis can aid understanding and decrease decisional uncertainty (65,79,80). Interactive AI-supported platforms can also facilitate more collaborative interaction between patients and could be used to deliver individualized information about treatment plans, possible side effects, follow-up care and lifestyle changes (81). This individualized data-driven approach not only enhances patient autonomy but also builds trust and satisfaction by ensuring that the care plan matches the patient values and expectations (28,81).

Optimizing resources and cutting healthcare costs

The use of AI for making predictions in surgical oncology has broad implications related to resource distribution in health care (82). Via categorizing patients according to the risk of recurrence and their response to treatment, AI allows for a more efficient utilization of diagnostic imaging, laboratory testing, and therapeutic interventions (80,83,84). Risk-adapted follow-up could prevent unnecessary imaging in persons at low risk, limiting radiation dose, clinical effort and cost (80). Equivalently, customized adjuvant therapy by means of AI predictions could potentially reduce the number of patients who receive unnecessary treatment, reducing drug cost and those burdened with treating medicine-associated complications

(61,85,86). At an institutional level, accurate prediction of outcomes can aid strategic planning with respect to clinical capacity (e.g., in oncology) and triage of patients at high risk (86,87). Where resources are few, AI-based triage tools prioritize guiding scarcer resource usage based on a patient's likelihood of benefit—thus driving equity and value-based care. Although the initial costs of investment in an AI system may be high, long-term savings from decreased overtreatment, optimized surveillance and increased clinical efficiency demonstrate its cost-effectiveness (80,86,87).

Challenges and Limitations

The performance of an AI model is closely related to the quality and representativeness of the training data it learns from (88). Clinical datasets for surgical oncology research are commonly fragmented, inconsistent or incomplete as a result of different institutional recording practices, imaging protocols and pathology reporting (21). Such problems result in noise, missing variable and low predictive accuracy (26). Heterogeneity is further derived from variations in patient characteristics, tumor biology, therapy patterns and surveillance (73,89). Algorithms developed on homogeneous or restricted datasets might unintentionally reflect systemic biases (overachieving with some patient subgroups that are over-represented and underperforming for others). For instance, insufficient representation of minority or low-resource populations could lead to biased prognostic estimations and widen current health inequalities (33,90). Moreover, small sample sizes (specially for rare tumor types) render the model less robust. The absence of uniform annotations, particularly in imaging and histopathology, restricts reproducible model development. The solution to these foundational limitations is strong data curation, harmonization and transparent reporting (91).

Deep learning based methods are typically treated as "black boxes", which means the predictions come with no explanation (40,41). Despite their superior performance over traditional models, these 'black box' models are not always readily interpretable, which slows the trust and adoption by clinicians (40,41). A lack of explainability is particularly concerning when it comes to high-stakes decisions, like advice on adjuvant therapy or increased surveillance intervals (39,92). With no explanation, providers may not trust AI-derived risk scores, especially when predictions contradict what is known or guidelines (93). Techniques such as saliency maps, SHAP values and attention models are being developed to increase the interpretability of those model by pointing out useful features behind predictions (33,94). There is, however, many deficiencies in the current tools and they needs improving before they can be used clinically. Optimizing this trade-off between predictive and transparency is a significant challenge for the translation of AI-based prognostic tools in routine surgical oncologic practice (39,45).

One of the long-standing drawbacks of AI models is poor generalization (24). Most algorithms are not trained or validated on data that encompasses the range of worldwide patient populations, typically being trained with single-center/regional datasets (23,95). Models can do well when tested internally, but can drop dead when deployed in external cohorts characterized by different demographics or genetics or environments (96). Variability in imaging hardware, pathology protocols as well as treatment procedures between centers also limit the potential for reproducibility (97). Validation in an external cohort, multicenter collaboration, and federated learning strategy are required to enhance generalizablement (97–99). The overarching lack of multi-institutional validation makes the clinical translation of AI prognostic tools still

unknown, preventing their integration into routine postoperative pathways (81).

For successful clinical deployment, AI tools need to be harmoniously embedded into current surgical and oncological workflows (100). However, several practical barriers remain. Experience Weighs In AI systems tend to require significant computational infrastructure, compatibility with electronic health records (EHRs) and real-time data processing — resources that aren't always part of the workflows in clinical settings (101). Moreover, AI tools could also interrupt workflows of clinicians as a need arises for an extra input data entry, new imaging protocols or unrecognized software platforms (102). Limited education on interpretation and possible medico-legal implications could also be a barrier for use. Prognostic tools need to be user-friendly, and should be able to function in different practice settings (37). If AI is to augment rather than confuse surgical decision-making, it will need to be co-developed with clinicians and include constant input from users. The incorporation of AI into postoperative prognostication presents a number of thorny ethical and regulatory issues. Privacy and security of patients, data is most critical, in particular for big data model training (43,103). Trust is crucial, and finding methods to consent well, anonymize data appropriately is very important. Inaccuracies in predictions from AI models also can result in unjust delivery of care, which might be detrimental for vulnerable groups (104,105). For this reason, open audits and fairness testing are essential to avoid any unintended injury. What's more, there is the risk of algorithmic error, with attendant medico-legal liability—especially if AI recommendations dictate important treatment decisions (103). The legal landscape of AI in healthcare continues to mature. Regulations from the FDA or EMA are slowly consolidating aspects regarding clinical validation, safety, performance tracking and post-deployment updates. Active monitoring and uniform reporting requirements will be critical to the accountability and safety integration into clinical practice (106).

Future Directions

One of the most promising frontiers involves XAI in surgical oncology. Although modern deep learning and more complex machine learning models exhibit excellent predictability, their "black box" nature reduces clinical confidence and acceptance. XAI techniques seek to achieve transparency by revealing which features, patterns or data points are determining model predictions. In reality, XAI might enable a surgeon or oncologist to learn why patients are predicted at high risk of recurrence or poor survival, and potentially make it easier for AI-generated insights to be absorbed into the clinical decision-making process. Methods including attention maps, feature importance scoring and counterfactual explanations can serve as intermediates between predicting well and being interpretable that provide clinician confidence and patient trust.

Another promising direction is creation of federated learning sytems such as access to global/multi-institution data. Older AI models frequently use single-center data for training and thus have a narrow generalizability. Federated learning allows AI to train on disparate datasets from multiple institutions without sharing patient data, maintaining privacy and increasing generalisability. International datasets across varying populations, imaging protocols and tumour types will improve model performance and equity. By learning from heterogeneous data, AI models increase the generalisability of predictions and stem bias in restricted local datasets. This approach is an added bonus for multi-institution collaborations as it will quicken the pace of innovation and validation of AI prognostic tools.

The furthermost front in AI-driven surgical oncology is real-time intraoperative prognostication. By combining AI with surgical imaging, pathology and intraoperative data streams, surgeons could be provided dynamic risk-assessment tools during tumor resection. For example, AI may be able to assess margin status including the effect of tumor heterogeneity or patterns of microvascular invasion in real time, guiding decisions as to degree of resection necessary or whether immediate adjuvant therapy is required. These technical abilities would change surgeries from simply anatomical resections to oncologically-sighted procedures and, in turn, reduce residual disease while maximizing outcomes after surgery.

Integration with Genomics, Proteomics and Liquid Biopsy. The next-generation prognostic models will need to combine the multi-omics (genomic, proteome, transcriptomic and metabolomic) data with AI and imaging based on clinical data. Integration of liquid biopsy information, such as the presence of circulating tumor DNA (ctDNA) or circulating tumor cells (CTCs), can offer on-time molecular perspective into residual disease or risk of recurrence. AI models that can integrate such heterogeneous data elements can potentially reveal subtle biological signals are predictive of relapse, resistance to therapy or survival. That kind of unification evolves from static clinicopathological models into a dynamic, biology-driven model that reflects the evolutive process of tumor and patient-specific risk profiles during any given time point. Together, these developments presage the coming era of precision-guided surgical oncology. In the end, AI-based prognostication will personalize surgical approach, surveillance frequency and adjuvant therapy to those most appropriate for the individual patient's tumor biology, risk category and response duration. Using transparent algorithms, federated learning, point-of-care insight in real time during surgery and multiomics correlation analysis, surgical oncology may change from a population-level practice to a personal level. This vision holds the prospect of better survival, less recurrence, less overtreatment and lower cost burden and resource use; it represents a paradigm shift in perioperative cancer care.

CONCLUSION

The admission of AI into prognostication in surgical oncology heralds a new era for the post-operative care of resected cancer patients. Evolving evidence suggests that AI (i.e., machine learning, deep learning, multi-omics integration) may have an improved performance compared with traditional prognostication not only in identifying patients with high risk of recurrence but also predicting survival and guiding management in the adjuvant setting or for surveillance across a range of solid tumors. There are several limitations to this study. Challenges in the areas of data quality and heterogeneity, interpretability, generalisation to new subjects or populations, integration within clinical workflows and ethical/regulatory concerns still limit the widespread adoption of AI-based tools into routine clinical care. It is important to overcome these limitations for fair, robust, and safe deployment in open-world scenarios. The potential of AI in surgical oncology depends on multidisciplinary partnerships between surgeons, data scientists, bioinformaticians, pathologists and healthcare authorities. These partnerships are essential for building and validating robust, explainable, clinicallyrelevant models across diverse populations and developing regulatory frameworks that protect patient privacy while encouraging innovation. Ultimately, AI-enhanced surgical oncology has the potential to revolute perioperative care with individualized surgical approaches, targeted

adjuvant therapy and personalized surveillance programs. By leveraging AI's predictive abilities alongside human experience, the field has the potential to advance a future where relapse is caught earlier and survival results are more successful. —patient care becomes more right-sized, less buttoned-up and more patient-centric.

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