

Artificial Intelligence in Robotic Surgery: Advancements, Applications and Future Scope

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Abstract: *Robotic surgery is evolving from surgeon-controlled teleoperation toward systems augmented by Artificial Intelligence (AI) that can perceive, assist, predict outcomes, and execute constrained subtasks under supervision. This paper presents a secondary-data review and conceptual systems analysis of primary literature (2018–2025) on AI in robotic surgery. The reviewed evidence indicates that deep learning (DL) and computer vision provide intraoperative scene understanding via instrument segmentation and depth estimation, enabling guidance overlays and lowering deployment complexity through multi-task learning. Navigation and mapping benefit from endoscopic datasets with synchronized 6DoF pose ground truth and topographical information, supporting benchmarking for localization and 3D reconstruction. Reinforcement learning (RL) is most credible for well-defined subtasks such as needle hand-off in suturing, where state/action spaces and safety constraints are tractable. Clinically, supervised autonomy has been demonstrated for laparoscopic intestinal anastomosis with quantified endpoints (e.g., leak pressure and lumen patency) alongside motion-compensated execution strategies. AI also supports surgical safety via AR overlays that localize hidden anatomy with millimeter-scale error and improves decision support through outcome prediction models that outperform traditional risk stratification (AUC gains) after robot-assisted prostatectomy. Despite these advancements, translation is constrained by dataset shift, clinical validation requirements, liability and accountability concerns, and privacy-legal constraints on surgical data (HIPAA/GDPR contexts). We propose a modular framework emphasizing sensor fusion, uncertainty-aware safety layers, human oversight, and lifecycle governance..*

Keywords: Robotic surgery

I. INTRODUCTION

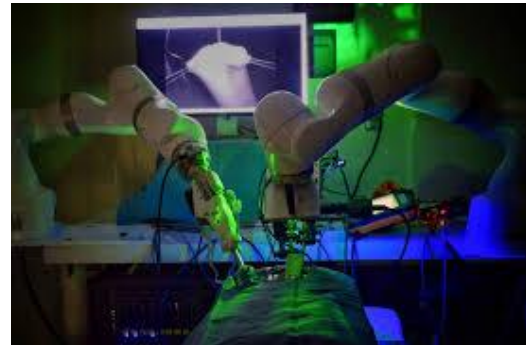
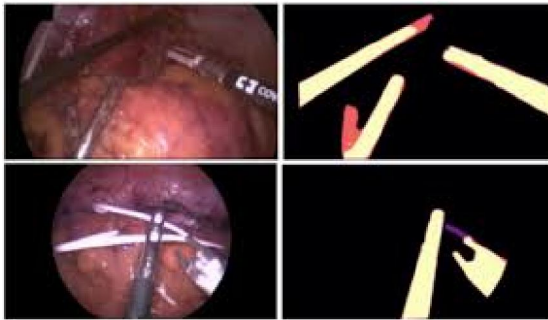
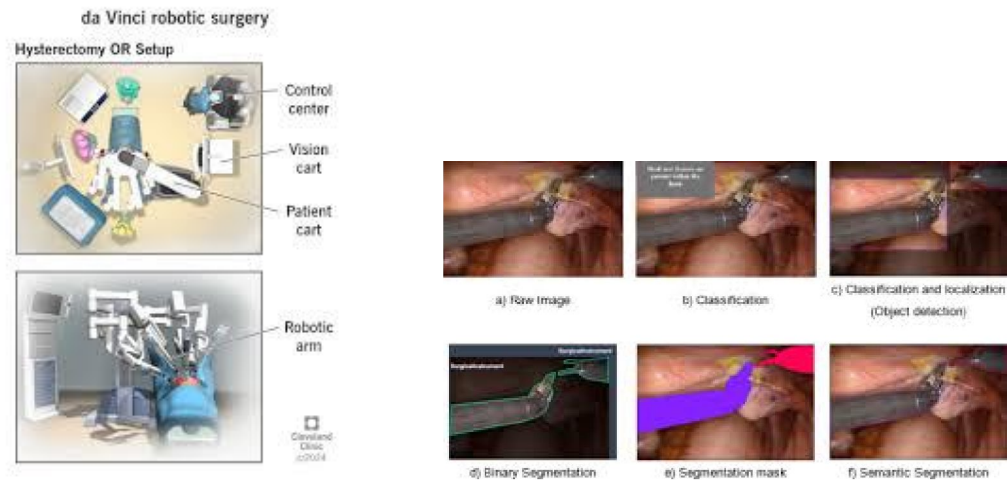
Robot-assisted minimally invasive surgery offers enhanced dexterity, tremor filtering, and improved visualization, but soft-tissue procedures remain challenging due to restricted access, limited field-of-view, deformable anatomy, and motion/visibility constraints. These challenges motivate AI modules that can (a) perceive surgical state (tools, tissue, depth), (b) support planning and decision-making, and (c) execute bounded tasks under surgeon oversight.

A clinically meaningful framing is **human-supervised autonomy**, where the surgeon approves autonomously generated plans and retains override authority while the robot executes subtasks with safety constraints. A prominent example is autonomous laparoscopic small bowel anastomosis performed in phantom and in vivo settings with explicit quality criteria (needle placement correction, suture spacing/bite size consistency, completion time, lumen patency, and leak pressure).

AI capability in robotic surgery can be organized as a layered stack:

- (1) **Data and sensing** (endoscopic RGB/stereo/near-infrared, robot kinematics, optional force/torque),
- (2) **Perception** (segmentation, depth, tracking, mapping),
- (3) **Decision** (planning, prediction, alerts),
- (4) **Control** (constraint-aware motion, virtual fixtures), and
- (5) **Governance** (validation, monitoring, controlled updates). This paper focuses on how primary studies demonstrate measurable progress across these layers and where limitations remain for safe clinical translation.





II. LITERATURE REVIEW OF PRIMARY SOURCES

The literature below summarizes **8 primary sources (2018–2025)** selected to align with required application areas: tumor detection, autonomous assistance, suturing, navigation, outcome prediction, and core enabling perception methods. Each item includes a DOI and a source link via citation.

Primary source set (with DOI/link):

Supervised autonomy for laparoscopic intestinal anastomosis — Saeidi *et al.*, *Science Robotics* (2022), doi:10.1126/scirobotics.abj2908. This work demonstrates autonomous plan generation with operator selection and in vivo porcine survival study evaluation using leak pressure, lumen patency, and timing metrics.

Multi-task perception: depth estimation + surgical tool segmentation — Huang *et al.*, *IEEE Transactions on Medical Robotics and Bionics* (2022), doi:10.1109/TMRB.2022.3170215. The paper proposes a unified framework to jointly estimate depth (self-/unsupervised) and segment tools, reporting SSIM and IoU/Dice performance with deployment complexity reduction.

Real-time instrument instance segmentation — Ángeles Cerón *et al.*, *Medical Image Analysis* (2022), doi:10.1016/j.media.2022.102569. The authors propose a lightweight single-stage instance segmentation model with attention and multi-scale fusion, emphasizing real-time performance and reporting large relative gains on challenge metrics (MI_DSC, MI_NSD).

Endoscopic navigation benchmarking dataset — Ozyoruk *et al.*, *Medical Image Analysis* (2021), doi:10.1016/j.media.2021.102058. This paper introduces EndoSLAM, addressing the scarcity of endoscopy data with



time-synchronized 6DoF pose and topographical ground truth, enabling benchmarking for pose/depth/SLAM and domain adaptation.

AR tracking for localization of critical anatomy in robotic thyroid surgery — Lee *et al.*, *Scientific Reports* (2020), doi:10.1038/s41598-020-65439-6. A vision-based tracking system overlays CT-derived AR models to localize the recurrent laryngeal nerve (RLN) during robotic thyroid surgery, reporting millimeter-scale localization error.

Reinforcement learning for suturing subtask automation (needle hand-off) — Varier *et al.*, *IEEE RO-MAN* (2020), doi:10.1109/RO-MAN47096.2020.9223543. The paper fragments suturing into manual and automated tasks and applies discrete RL (Q-learning), reporting RMSE values for learned trajectories.

Outcome prediction in robot-assisted radical prostatectomy (RARP) — Rajih *et al.*, *Journal of Robotic Surgery* (2025), doi:10.1007/s11701-025-02786-4. The study compares ML models against traditional risk stratification (D’Amico, CAPRA), reporting improved AUC for biochemical recurrence prediction.

Tumor detection and margin assessment using hyperspectral imaging + DL — Bali *et al.*, *Cancers* (2025), doi:10.3390/cancers17101617. The paper reports a workflow integrating HSI with deep learning and 3D modeling for label-free tumor margin delineation in head and neck squamous cell carcinoma (HNSCC), including accuracy and sensitivity metrics and dataset notes (datacubes).

Table I. Comparison of key studies (methods, datasets, metrics, limitations).

(Assumption policy: if a paper does not specify details in the openly accessible abstract/summary lines (e.g., exact fps, compute hardware), it is marked “unspecified.”)

Authors (Year)	Application	AI/Tech Methods	Dataset / Setting	Key Results (reported)	Limitations (reported/implicit)
Saeidi <i>et al.</i> (2022)	Autonomous assistance + anastomosis	CNN tracking + NIR marker tracking + plan generation supervised execution	Porcine in vivo (STAR n=4; control n=1) + phantom	Leak pressure 0.69 ± 0.59 psi ; lumen patency 88.75 ± 4.79% ; completion time 62.03 ± 5.32 min vs 25.6 min control; CNN test accuracy 91.52%	Small in vivo cohort; workflow relies on markers; slower due to conservative safety + supervision steps
Huang <i>et al.</i> (2022)	Perception for autonomy	Multi-task DL for depth + tool segmentation	Two datasets; 400 images labeled for segmentation	Depth SSIM mean 72.8 ; Segmentation IoU/Dice 74.92/85.63 ; time 0.35 (units as reported)	Dataset shift risk; compute and latency constraints; some details (hardware) unspecified
Angeles Cerón <i>et al.</i> (2022)	Perception	Single-stage instance segmentation with attention + multi-scale fusion	ROBUST-MIS frames (>10,000 frames noted)	Reports > 44% improvement on MI_DSC and 39% on MI_NSD vs prior top team; real-time performance claimed	Absolute fps and hardware in open preview: unspecified; robustness under OR domain shift still a barrier
Ozyoruk <i>et al.</i> (2021)	Navigation + mapping	Dataset + Endo-SfMLearner (monocular depth/pose with spatial attention)	EndoSLAM dataset: ex vivo porcine organs + phantom colon; 6DoF pose + topography	Establishes 6DoF pose + topographical ground truth; supports benchmarking for SLAM/3D reconstruction and domain adaptation	Ex vivo/phantom vs real OR domain shift; full clinical validation not the goal of dataset paper
Lee <i>et al.</i> (2020)	Navigation + AR safety	Vision-based tracking + SLAM-like AR alignment;	Robotic thyroid surgery; 11 RLNs	Mean RLN AR-to-actual distance 1.9 ± 1.5 mm (0.5–3.7 mm); no RLN palsy reported in	Small cohort; deformation incompensation limited;



Authors (Year)	Application	AI/Tech Methods	Dataset / Setting	Key Results (reported)	Limitations (reported/implicit)
		CT-derived AR models		cohort	OR integration constraints
Varier <i>et al.</i> (2020)	Suturing subtask	Discrete RL (Q-learning) for needle hand-off	dVRK-based suturing task; user trajectories	RMSE reported [0.0044, 0.0027, 0.0020] mm in R ² ; demonstrates feasibility of learned policy	Subtask-only; sim-to-real and broader clinical endpoints unspecified
Rajih <i>et al.</i> (2025)	Outcome prediction	ML models vs D'Amico/CAPRA stratification	Retrospective 758 RARP (2014-2018)	Pre-op ML AUC 0.783 vs D'Amico 0.692 (12-mo BCR); post-op model AUC 0.847 (12-mo) and 0.863 (24-mo)	Retrospective/single-system risks; external validation and drift monitoring needed
Bali <i>et al.</i> (2025)	Tumor detection	HSI + CNN models + tumormodeling + histopath ground truth	Ex vivo 3DHNSCC; n=712 datacubes	Overall accuracy 0.98 , tumor sensitivity 0.93 ; throughput <10 min stated	Proof-of-concept; ex vivo; prospective intraoperative integration required

III. METHODOLOGY AND TECHNOLOGY OVERVIEW

Methodology (secondary-data review + conceptual analysis):

This paper synthesizes findings from primary sources through (i) structured extraction of reported datasets, methods, and metrics and (ii) conceptual systems analysis that maps those findings onto an implementable architecture for AI-enabled robotic surgery. No new data collection or model training/testing is performed; all quantitative values are reported as presented in the cited sources.

Technology overview (AI components mapped to surgical system needs):

Machine Learning (ML) for prediction: ML models using clinical variables can support patient counseling and follow-up planning; in robot-assisted prostatectomy, ML can outperform traditional stratification in AUC for biochemical recurrence prediction.

Deep Learning (DL) + Computer Vision: Vision is the dominant sensing modality in minimally invasive robotic surgery. Joint depth + segmentation approaches can reduce deployment complexity versus sequential pipelines while enabling downstream functions such as overlay guidance and safe motion constraints.

Reinforcement Learning (RL): RL is best positioned for bounded subtasks (needle hand-off, grasp transitions), where an explicit reward can capture correctness and safety, and where the surgeon can supervise or gate autonomy.

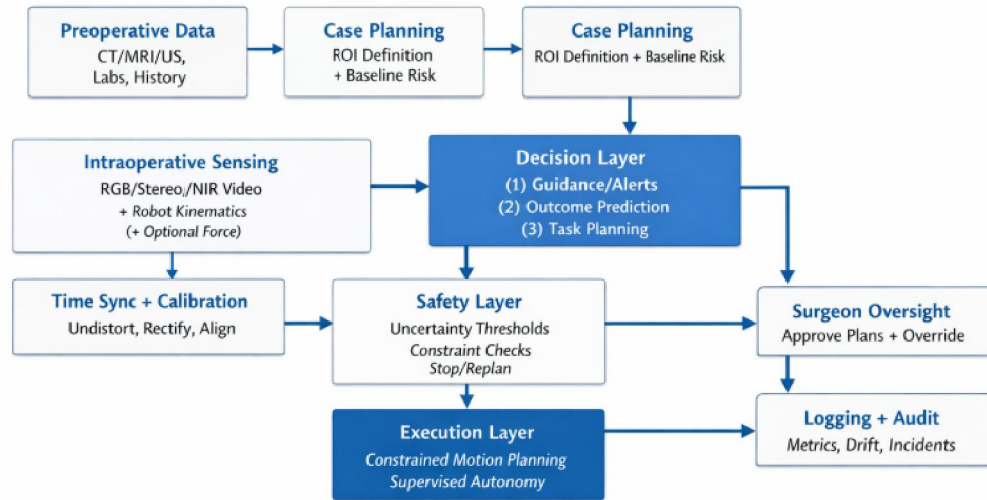
Sensor fusion: Clinically relevant autonomy requires synchronization of endoscopic video with robot kinematics and (where available) additional sensing (e.g., NIR tracking, force proxies). The autonomous anastomosis system integrates tracking and planning to execute during low-motion phases (breathing rest) and can trigger replanning under marker displacement thresholds.

Proposed Framework and System Architecture

This section proposes a submission-ready conceptual framework that is consistent with the “human-supervised autonomy” pattern demonstrated in autonomous anastomosis and is compatible with perception modules (segmentation/depth), navigation datasets, AR overlays, and outcome prediction.

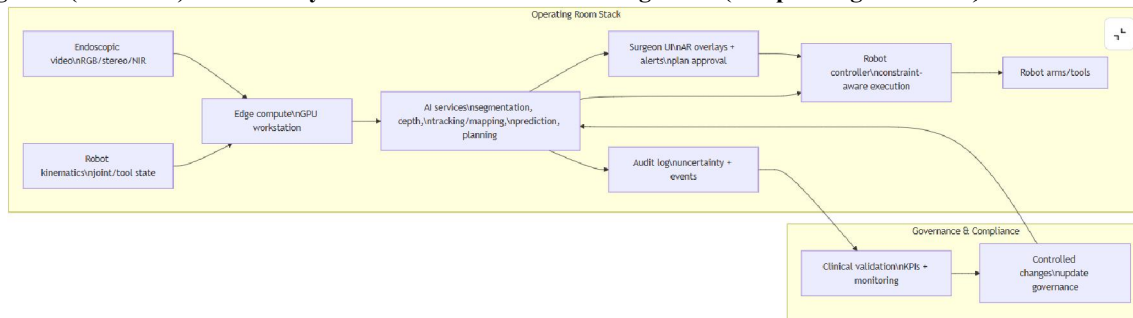


Figure 1 (Mermaid). Human-supervised AI-enabled robotic surgery flow (conceptual).



Design grounding: The “plan selection by operator → autonomous execution → replanning triggers” pattern aligns with the anastomosis autonomy strategy and its explicit deformation thresholds.

Figure 2 (Mermaid). Modular system architecture for OR integration (compute + governance).

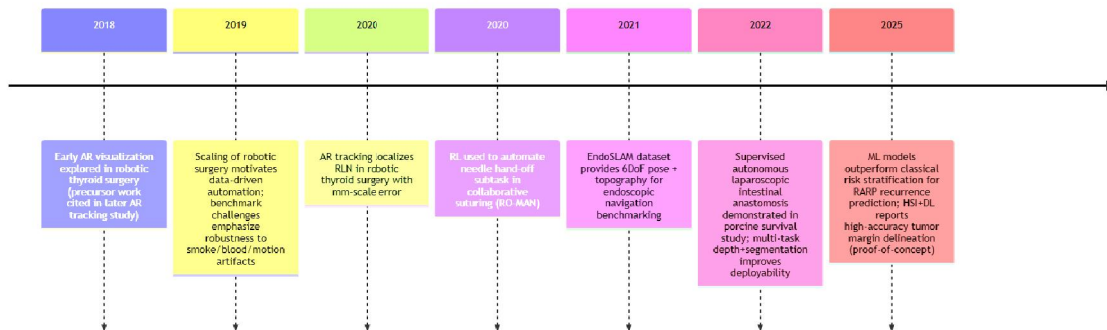


Implementation note (no experiments): This architecture is a conceptual integration blueprint based on validated patterns in the cited literature; implementation details (latency budgets, camera calibration specifics, compute hardware) will vary by platform and are **unspecified** unless explicitly reported by a source.

Figure 3 (Mermaid). Timeline of selected milestones (2018–2025) referenced in this paper.



AI in Robotic Surgery: Research Milestones (2018-2025)



Timeline evidence links: 2018 precursor AR study is cited within the 2020 AR tracking paper’s reference list; 2020–2025 milestones are directly supported by the primary studies summarized in the literature review.

IV. APPLICATIONS AND DISCUSSION

Tumor detection and margin assessment

Hyperspectral imaging (HSI) combined with DL can provide label-free tissue differentiation for intraoperative decision-making. In head and neck squamous cell carcinoma, the HSI + DL + 3D modeling workflow reports **overall classification accuracy 0.98** and **tumor sensitivity 0.93**, with dataset detail **n = 712 datacubes** co-registered to histopathological ground truth. The study positions the workflow for “real-time” intraoperative feasibility by emphasizing rapid assessment and minimal workflow disruption (reported throughput statements).

Autonomous assistance and supervised autonomy

Autonomous laparoscopic bowel anastomosis provides a strong benchmark because it has objective quality endpoints. In porcine in vivo experiments, the autonomous system reports **leak pressure 0.69 ± 0.59 psi** and **lumen patency $88.75 \pm 4.79\%$** , alongside a longer completion time **62.03 ± 5.32 min** versus **25.6 min** for the control, attributed to additional planning, supervision, and conservative safety limits. These results illustrate a key translational trade-off: early autonomy prioritizes safety and consistency, often at the expense of time efficiency.

The same study reports **CNN-based motion state test accuracy 91.52%** and uses marker tracking to coordinate suturing with breathing cycles and to trigger replanning when marker displacement norms exceed thresholds (e.g., 3 mm). This highlights how autonomy in soft tissue depends on reliable state estimation and explicit safety triggers, not merely a learned policy.

Suturing and reinforcement learning

A pragmatic near-term use of RL is **subtask automation**, where the environment is constrained and the surgeon can remain “in the loop.” In collaborative suturing, the needle hand-off task is automated using discrete RL (Q-learning) trained from user trajectories; the study reports RMSE values [**0.0044, 0.0027, 0.0020**] mm in R^3 for policy-derived trajectories relative to user-defined paths (as reported). This demonstrates feasibility for precision micro-actions while leaving full-procedure autonomy as an open challenge.

Navigation, mapping, and AR guidance

Navigation in deformable endoscopic scenes requires both algorithms and benchmarks. The EndoSLAM dataset directly addresses the shortage of endoscopy data with synchronized **6DoF pose ground truth** and **high precision topographical information**, built from ex vivo porcine organs and a phantom colon with CT ground truth. This enables quantitative benchmarking for pose/depth/SLAM and supports research into domain adaptation and reconstruction evaluation.

For intraoperative safety guidance, AR overlays can help identify anatomy that is difficult to visualize directly. In robotic thyroid surgery, a vision-based tracking AR system reports a mean RLN AR-to-actual distance **1.9 ± 1.5**



mm (0.5–3.7 mm) across 11 RLNs, with *no RLN palsy reported* in the tested cohort, supporting feasibility for localization assistance (subject to broader validation requirements).

Perception: instrument segmentation and depth estimation

Perception is foundational for safe assistance and autonomy. A multi-task approach for laparoscopic images reports depth performance using SSIM (mean **72.8** for the fused model) and segmentation performance IoU/Dice (**74.92/85.63**) with reported timing (**0.35**, units as stated). The design motivation is that joint learning reduces pipeline complexity and improves deployability when depth labels and segmentation ground truth are scarce.

Instance segmentation for instruments is similarly emphasized as a real-time requirement in minimally invasive settings; the cited work proposes a single-stage approach with attention and multi-scale fusion and reports large *relative* improvements on challenge metrics (e.g., **>44%** on MI_DSC and **39%** on MI_NSD versus prior top team performances), positioning attention-based single-stage systems as candidates for real-time OR deployment. (Absolute fps and hardware specifics in the accessible preview are **unspecified**.)

Outcome prediction and data-driven decision support

Outcome prediction is a high-impact “low-control-risk” AI application because it does not directly actuate the robot. In robot-assisted radical prostatectomy, the ML model using only pre-surgical variables reports **AUC 0.783** for 12-month biochemical recurrence prediction, outperforming D’Amico classification (**AUC 0.692**, $p < 0.001$). A more comprehensive post-operative model incorporating pathological variables reports **AUC 0.847** (12-month BCR) and **AUC 0.863** (24-month BCR). These results support ML-based personalization of counseling and surveillance planning, subject to external validation and monitoring for drift.

Table II. Cross-application performance metrics (synthesis).

Application	Representative metric(s)	Reported range / example	Interpretation for deployment
Autonomous soft-tissue suturing/anastomosis	Leak pressure, lumen patency, completion time	Leak pressure 0.69 ± 0.59 psi , patency 88.75 ± 4.79% , time 62.03 ± 5.32 min	Autonomy is benchmarkable; early systems favor safety/consistency over speed
Tool segmentation + depth	IoU/Dice, SSIM, timing	IoU/Dice 74.92/85.63 , depth SSIM 72.8 , time 0.35	Multi-task perception supports overlays and constraint-aware control; latency/hardware may be limiting
Instrument instance segmentation	Challenge metric gains, real-time emphasis	>44% MI_DSC, 39% MI_NSD relative gains	Robustness and speed are key; absolute fps/hardware often underreported publicly
Navigation benchmarking	Dataset providing pose/topography	EndoSLAM provides 6DoF pose + topography on ex vivo porcine + phantom	Benchmarks are needed for reproducibility and safety arguments
AR safety overlay	Localization error	RLN localization 1.9 ± 1.5 mm mean distance	AR is promising for hidden anatomy guidance; must handle deformation and workflow integration
Outcome prediction	AUC (discrimination)	AUC 0.783 (pre-op), 0.847–0.863 (post-op)	Decision support can be adopted earlier than actuation; requires monitoring and bias checks
Tumor margin detection	Accuracy, sensitivity	Accuracy 0.98 , sensitivity 0.93 ; n=712 datacubes	High promise for margin guidance; clinical integration needs prospective intraoperative validation



Application	Representative metric(s)	Reported range / example	Interpretation for deployment
RL subtask automation	RMSE of trajectory / policy imitation	RMSE [0.0044, 0.0027, 0.0020] mm	RL is suitable for bounded subtasks with human gating; procedure-level autonomy remains hard

Limitations, Ethical Considerations, and Legal/Regulatory Issues

Technical limitations and validity threats:

The dominant technical limitation across applications is **dataset shift**—models trained on particular camera systems, lighting conditions, tissue appearances, and surgeon techniques can degrade under real OR variability. This is visible indirectly through the field’s strong emphasis on robustness datasets/challenges and on reducing the complexity of deploying multi-stage pipelines.

Safety and accountability in autonomy:

When AI influences robot motion, safety constraints and conservative speed limits are commonly used to reduce collision risk and unintended tissue interaction. The autonomous anastomosis study explicitly attributes slower performance to additional planning, supervision time, safe tool rotations, and conservative speed limits. This reinforces that autonomy research must satisfy safety-first performance envelopes, not just task completion.

Regulatory: lifecycle management and controlled updates (FDA PCCP):

For AI-enabled device software functions, the U.S. Food and Drug Administration recommends Predetermined Change Control Plans (PCCPs) that describe planned modifications, validation/implementation methods, and impact assessments, reviewed as part of marketing submissions to support iterative improvements while maintaining safety and effectiveness. This is highly relevant to robotic surgery AI because models may require updates to address drift or new data.

EU AI Act: staged applicability and high-risk obligations:

The European Commission states the AI Act entered into force on **1 August 2024**, and provides an application timeline in which high-risk AI systems (including those embedded into regulated products) have staged compliance deadlines, with the Act fully applicable two years later and certain provisions phased earlier/later. In surgical robotics, this implies that clinical AI components may face high-risk obligations depending on integration into medical devices and intended use.

Ethics and governance (WHO):

The World Health Organization guidance emphasizes that AI for health must put ethics and human rights at the center of design, deployment, and use, identifying ethical risks and recommending governance approaches to ensure accountability to health workers and affected communities. These principles map directly to robotic surgery contexts where clinicians may rely on AI overlays and predictions and where errors can have immediate harm.

Privacy and health data constraints (GDPR/HIPAA context):

Robotic surgery AI requires video, device telemetry, and outcome data—often sensitive medical information. Comparative analyses of healthcare privacy frameworks highlight that the HIPAA Privacy Rule emphasizes legal obligations for protecting ePHI/PHI in North America, while GDPR mandates broader consent and accountability measures in Europe, reflecting differing compliance environments that impact multi-site model training and data sharing. In practical terms, this constrains dataset aggregation and makes privacy-preserving workflows (de-identification, governance, audit trails) critical for AI development and external validation.



V. CONCLUSION AND FUTURE SCOPE

Conclusion:

Across primary sources (2018–2025), AI in robotic surgery shows the most credible progress in modules that can be validated with objective measurements: supervised autonomy in soft-tissue suturing/anastomosis (leak pressure, lumen patency), real-time perception (IoU/Dice, SSIM), navigation benchmarking (pose/topography ground truth), AR safety localization (millimeter-scale error), outcome prediction (AUC improvements), and tumor margin detection (accuracy/sensitivity against histopathology). Collectively, these results support the near-term trajectory of **human-supervised autonomy** and **AI-assisted decision support**, rather than fully autonomous surgery.

Future scope (research and deployment priorities):

Future research with the highest translational value includes: (i) multi-center validation and domain generalization methods, (ii) uncertainty-aware safety gating and fail-safe behavior, (iii) improved benchmarks and shared datasets for deformable navigation/mapping, (iv) privacy-aware cross-institution learning pipelines compatible with GDPR/HIPAA constraints, and (v) lifecycle governance enabling safe updates in line with PCCP-style controls and ethical accountability principles.

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