WISELEAF SCIENTIFIC VENTURES

SMART HEALTHCARE REVOLUTION: AI STRATEGIES FOR SUPERIOR GLOBAL HEALTH

CHAPTER 3- ROBOTIC SURGERY ENHANCED BY ARTIFICIAL INTELLIGENCE

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ABSTRACT

Robotic surgery began as an exercise in mechanical precision and is now becoming an exercise in data. This chapter traces that shift from the adapted industrial arm used for CT-guided brain biopsy in 1985, through ROBODOC, AESOP, ZEUS and the da Vinci system, to the current generation of platforms, including da Vinci 5, Versius, Hugo RAS, Mako-type orthopaedic arms and the Indian SSI Mantra. The levels-of-autonomy framework proposed by Yang and colleagues in 2017 is used to organise the discussion. A scoping review of 129 intraoperative artificial intelligence (AI) studies found that 75% sat at the lowest level of assistance and none had reached clinical investigation in humans. The main AI components are examined in turn: instrument and anatomy segmentation, surgical phase recognition on datasets such as Cholec80, skill assessment from kinematic and video data (JIGSAWS and automated performance metrics), registration and augmented reality, and haptic feedback. Autonomous milestones are appraised critically, from the Smart Tissue Autonomous Robot (STAR) anastomoses of 2016 and 2022 to the 2025 SRT-H system that completed the clipping and cutting phase of cholecystectomy on eight ex vivo gallbladders. Telesurgery has moved from the 2001 transatlantic operation to human procedures over several thousand kilometres, and Indian demonstrations with SSI Mantra are part of that record. The clinical evidence is more sober than the marketing. The ROLARR trial showed no significant reduction in conversion to open surgery, and analyses of United States adverse-event reports show recurring device malfunctions. Costs, training, liability and equitable access are discussed with particular reference to India. The chapter argues that the near-term value of AI lies in measurement, feedback and safety monitoring rather than in replacing the surgeon.

Keywords: robotic surgery; surgical data science; levels of autonomy; computer vision; telesurgery; SSI Mantra

1. Introduction

A surgical robot, in the form most surgeons know it, is a sophisticated set of motorised instruments that does exactly what the surgeon's hands tell it to do. It filters tremor, scales motion, restores wristed movement inside the abdomen and gives a magnified three-dimensional view. It does not, in its standard clinical configuration, decide anything. That description has held for a quarter of a century, and during that time robotic assistance has spread from prostatectomy and hysterectomy into common general surgical procedures [1].

What has changed in the last decade is that the robot has become a recording instrument as well as an operating one. Every movement of every arm is logged as kinematic data. Every second of the endoscopic image is available as video. Energy activations, instrument exchanges and console events are timestamped. Maier-Hein and colleagues gave this body of information a name, **surgical data science**, and argued that its systematic capture and analysis could do for surgery what data infrastructure had already done for other parts of medicine [2]. Hashimoto and colleagues, writing at about the same time, set out both the promise and the hazards of applying machine learning to this material, and warned against expecting more from it than the data could support [3].

This chapter examines what artificial intelligence (AI) actually contributes to robotic surgery as of late 2026. The question is narrower than it sounds. Much of what is described as "AI-enhanced" robotic surgery is either conventional engineering (motion scaling and tremor filtering are control theory, not learning), or research that has not left the laboratory. A 2023 scoping review of intraoperative AI applications in robotic surgery found 129 studies, all at the earliest "idea" stage of the IDEAL framework for surgical innovation, with no clinical investigations in humans at all [4]. That finding should frame everything that follows. The interesting developments are real, but most of them are a long way from the operating list.

The chapter proceeds historically and then thematically. Section 2 recounts how industrial manipulators became surgical platforms. Section 3 surveys current commercial systems, including the Indian SSI Mantra. Section 4 introduces the levels-of-autonomy framework that has become the standard vocabulary for this field. Section 5, the longest, examines the AI components themselves: perception, phase recognition, skill assessment, registration and haptics. Sections 6 and 7 cover autonomous milestones and telesurgery. Sections 8 to 12 turn to the evidence on outcomes and cost, safety and liability, training, Indian adoption and ethics. Federated learning across hospitals, which matters for training surgical AI on multi-centre video without pooling it, is treated in Chapter 8 and is mentioned here only in passing.

2. From Industrial Arms to Surgical Platforms

2.1 Neurosurgery and orthopaedics: the precision robots

The first documented surgical use of a robot was a neurosurgical biopsy in 1985, performed with an adapted PUMA 560 industrial manipulator [5]. Kwoh and colleagues described the system in 1988 as a robot with improved absolute positioning accuracy for CT-guided stereotactic brain surgery [6]. The robot did not cut anything. Its job was to point a cannula at a target more accurately than a stereotactic frame adjusted by hand, which made it, in modern terms, a positioning device rather than an operating one.

Orthopaedics followed for a simple reason: bone does not move. ROBODOC, first used to prepare the femur in human hip replacement in 1992 [5], milled the femoral canal for cementless hip prostheses according to a plan made on preoperative CT [7]. Its development was unusually well documented. A canine trial in 26 dogs between May 1990 and September 1991 reported no intraoperative complications, and in laboratory comparisons cracking occurred in 5 of 15 manually broached control specimens and in none of the robot-milled ones [8]. Primary and revision hip replacement series were reported later in the decade [9]. ROBODOC established a pattern that is still visible in orthopaedic robotics: register the robot to preoperative imaging, then execute a plan within tight geometric limits.

2.2 Laparoscopy and the master-slave model

Soft-tissue surgery took a different route. Its first robots were assistants to laparoscopic surgeons, not replacements for any part of the procedure. Computer Motion's AESOP, a robotic arm that held and moved the laparoscope, removed the need for a human camera assistant and received approval from the United States Food and Drug Administration (FDA) in 1994 [5]. Computer Motion's ZEUS and Intuitive Surgical's da Vinci then introduced the master-slave design in which the surgeon sits at a console and controls instruments mounted on patient-side arms. The da Vinci system received FDA clearance for general laparoscopic surgery in 2000 [5], and after the two companies merged in 2003 it became, for many years, effectively the only soft-tissue platform in clinical use.

ZEUS had one more moment of fame. In September 2001, surgeons in New York removed the gallbladder of a patient in Strasbourg, using a ZEUS system connected over a dedicated high-speed fibre-optic link; the operation was reported in *Nature* and became known as Operation Lindbergh [10]. The same group later described the feasibility work behind it and its possible applications [11]. Telesurgery then went quiet for almost two decades, for reasons discussed in Section 7.

The history matters for a reason beyond chronology. Each early system was built around a single, well-defined capability: accurate pointing, accurate milling, a steady camera, a

dexterous wrist. None was built to learn. The AI layer discussed in this chapter is being added to platforms whose architecture was designed for teleoperation, and many of its present limitations follow from that fact.

3. Contemporary Platforms

The commercial field has widened considerably in the past decade. Table 3.1 summarises the main platforms discussed in this chapter. It is selective, and it reports regulatory milestones as the manufacturers or regulators describe them.

Table 3.1: Selected robotic surgical platforms, regulatory milestones, specialties and data or AI features

Platform (maker)	Milestone and year	Main specialties	Data and AI-related features as described by the maker or reviewers
da Vinci 5 (Intuitive Surgical, USA)	FDA 510(k) clearance, 14 March 2024 [12]	Urology, general, gynaecology, thoracic (adults) [13]	Optional force-feedback instruments; computing power stated as more than 10,000 times that of da Vinci Xi, intended initially for video review and coaching features [12,13]
Versius (CMR Surgical, UK)	CE mark 2019; FDA De Novo authorisation for cholecystectomy, 15 October 2024 [14]	General soft-tissue minimal access surgery	Modular, portable bedside units; open console; software updates and surgeon and hospital apps providing case data [14]
Hugo RAS (Medtronic, USA)	FDA clearance for prostatectomy, nephrectomy and cystectomy, 3 December 2025 [15]	Urology; used for gynaecology and general surgery outside the USA [15,16]	Linked to the Touch Surgery ecosystem with AI-based post-operative case insights, which the maker states are not intended to direct surgery [15]
Mako (Stryker, USA)	Among the robotic systems with US clearance for total hip arthroplasty [17]	Orthopaedics (hip and knee arthroplasty)	Image-based planning; haptic boundaries constrain the surgeon-guided cutting tool to the planned volume [17]
SSI Mantra (SS Innovations, India)	First installed clinically in July 2022; reported by the maker as CDSCO-approved for telesurgery [18,19]	Urology, gynaecology, general, thoracic and cardiac surgery [20,21]	Four robotic arms; open-face 3D console; remote tele-surgeon console used for telesurgery [22,23]

The **da Vinci 5**, cleared by the FDA on 14 March 2024, introduced optional force-sensing instruments to Intuitive's multiport platform [12]. In preclinical testing the company reported up to 43% less force on tissue when force feedback was used [12]. A device review by the Society of American Gastrointestinal and Endoscopic Surgeons (SAGES) adds an instructive caveat. The confirmatory clinical investigation enrolled 53 subjects across four specialties, and it found an increase in unplanned readmissions for vaginal bleeding within 30 days compared with the predicate device; as a result, the force-feedback needle drivers are contraindicated for suturing in hysterectomy and myomectomy [13]. A feature introduced to make surgery gentler produced, in one setting, a safety signal that restricted its use. The episode shows why new

sensing and feedback capabilities need clinical evaluation in their own right, however intuitive their benefit appears.

Versius took a different design approach, with separate modular arms on mobile carts that can be moved between theatres. CMR Surgical received FDA marketing authorisation through the De Novo pathway on 15 October 2024 for cholecystectomy in adults aged 22 years and older, and stated that more than 26,000 procedures had been performed with the system worldwide by that date [14]. Medtronic's **Hugo RAS** received FDA clearance on 3 December 2025 for prostatectomy, nephrectomy and cystectomy on the basis of the Expand URO investigational device exemption study; outside the United States the system had already been used in more than 30 countries [15]. Early clinical reports appeared from 2023, such as a first series of one left and two right colectomies completed without intraoperative complications or conversion [16]. The Hugo announcement is also notable for how carefully it describes the AI: post-operative "case insights" are offered through the Touch Surgery platform, with an explicit statement that they are not intended to direct surgery or aid diagnosis [15]. That wording reflects the regulatory reality. Analytic features that review a finished case face a lighter burden than features that influence the operation in progress.

In orthopaedics, systems such as **Mako** combine preoperative image-based planning with haptic boundaries, so that the surgeon moves the cutting tool by hand while the arm resists movement outside the planned bone volume [17]. These are the clearest examples in routine use of what the autonomy framework in Section 4 calls robot assistance.

The **SSI Mantra**, developed by SS Innovations under the cardiac surgeon Sudhir Srivastava, is the first surgical robotic system designed and manufactured in India [22]. Its first clinical installation was at the Rajiv Gandhi Cancer Institute and Research Centre in Delhi in July 2022 [18]. A single-centre series from that institution described 156 uro-oncology patients operated on between July 2022 and September 2023, including 77 radical prostatectomies and 39 radical cystectomies, with one conversion to open surgery caused by a system malfunction and no system-related intraoperative injuries [20]. A larger retrospective multi-centre study, classified at IDEAL stage 2b, reported 3,694 consecutive cases across 78 Indian centres between February 2023 and April 2025, with an overall conversion rate of 4.1% (95% CI 3.6 to 5.0%), intraoperative adverse events in 0.6% and a median hospital stay of 3 days [21]. By April 2026 the company reported more than 10,500 procedures and over 200 installed systems in eleven countries [24]. These are early, largely company-associated data without randomised comparison. They nevertheless amount to a more substantial evidence base than many newer platforms possessed at a similar stage.

4. Levels of Autonomy

Discussions of "autonomous surgery" were confused for years by the lack of shared terms. In 2017 Yang and colleagues proposed, in an editorial in *Science Robotics*, a six-level scale for medical robots modelled loosely on the levels used for self-driving cars [25]. Figure 3.1 presents the scale as a dial rather than a ladder, to emphasise that control passes gradually from human to machine and that the boundaries between levels are not sharp.

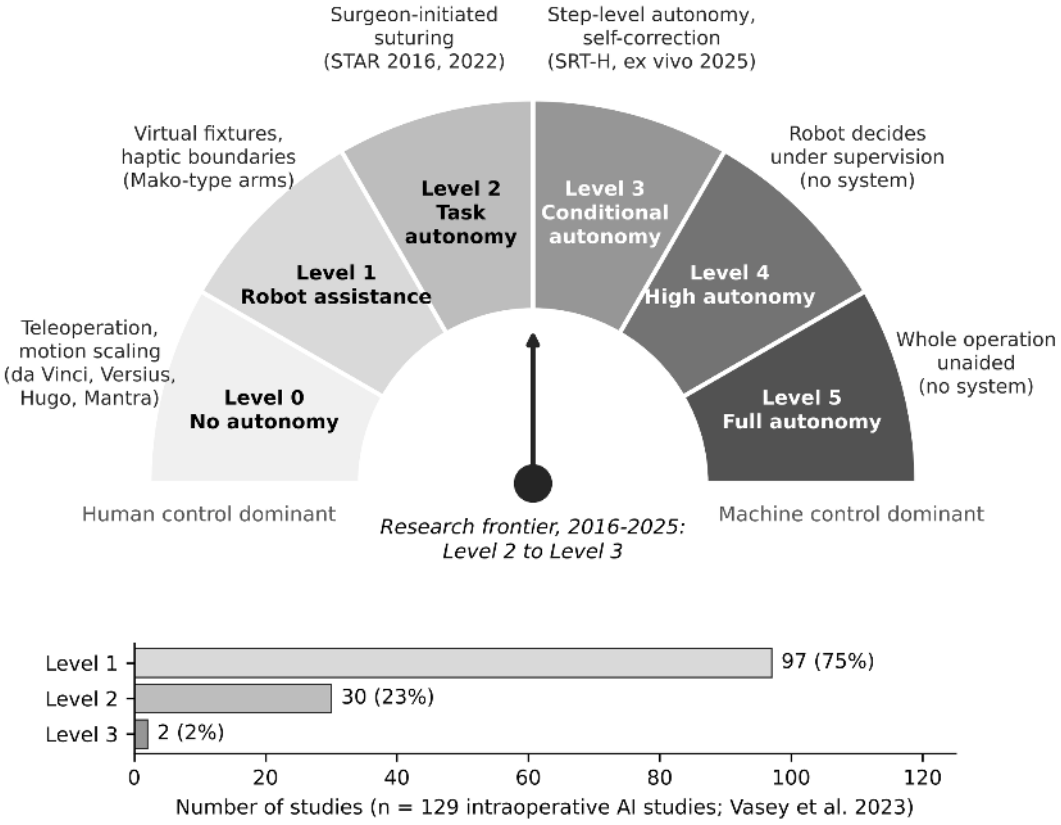

Figure 3.1: The six levels of autonomy for medical robots proposed by Yang et al. [25], drawn as a control dial, with representative systems at each level; the placement of SRT-H at Level 3 is the author's interpretation. The lower panel shows the distribution of 129 intraoperative AI studies in robotic surgery by autonomy level, from Vasey et al. [4].

At **Level 0** the robot has no autonomy: it follows the surgeon's commands, and features such as motion scaling still reproduce the surgeon's intended motion. Almost all soft-tissue robotic surgery performed today sits here. At **Level 1**, robot assistance, the robot provides mechanical guidance while the human keeps continuous control; virtual fixtures and haptic boundaries are the standard examples. At **Level 2**, task autonomy, the surgeon initiates a discrete task, such as

a running suture along a line the surgeon has indicated, and the robot performs it under supervision. At **Level 3**, conditional autonomy, the system generates strategies and the human selects or approves them, so the robot can perform a task without close moment-to-moment oversight. **Level 4**, high autonomy, would allow the robot to make medical decisions under the supervision of a qualified doctor, which the authors compared to a resident working under an attending surgeon. **Level 5**, full autonomy, would need no human at all; the authors placed it in the domain of science fiction [25].

The framework is useful for two reasons. It separates the question of *how much the machine decides* from the question of *how sophisticated its software is*. A Level 1 orthopaedic arm with a simple geometric boundary can be clinically mature, whereas a Level 2 deep-learning suturing system can be scientifically impressive and clinically unready. It also clarifies that legal and regulatory responsibility shifts as levels rise. At Levels 0 and 1, the surgeon is plainly responsible for the operation. From Level 3 upwards the robot chooses among options, and responsibility begins to be shared with the manufacturer and the designers of its decision logic [25].

The scale has weaknesses. It blends motor autonomy, what the robot does with its arms, with cognitive autonomy, what it recognises and decides; a robot could in principle recognise anatomy with great sophistication while executing nothing on its own, a distinction that matters in discussions of how surgery might progress towards autonomous actions [26]. “Level 2” also covers an enormous range, from an instrument server that hands over the right tool to a robot that sutures bowel. One of the earliest clinical examples of partial autonomy was in fact an instrument server: Treat and colleagues reported initial clinical experience in 2006 with a partly autonomous robotic instrument server that handled surgical instruments for the operating team [27]. The lower panel of Figure 3.1 shows where research actually stands. Of the 129 studies in the scoping review by Vasey and colleagues, 97 (75%) were at Level 1, 30 (23%) at Level 2 and only 2 (2%) at Level 3. Ninety per cent were performed in silico or on inorganic materials, 7% on ex vivo organic tissue and 3% in live pigs [4].

5. The AI Components of a Robotic Operating Room

5.1 A perception, planning and action pipeline

It helps to think of an AI-enabled robot in terms borrowed from autonomous vehicles: sensing, perception, planning and action, with the surgeon in a supervisory loop (Figure 3.2). Sensing is the raw data: stereo endoscopic video, instrument kinematics, force or torque signals where available, and preoperative imaging. Perception converts these into meaningful states, such as which pixels belong to which instrument, which structure is the cystic duct, and which phase of the operation has been reached. Planning decides what should happen next, whether that is a suggestion to the surgeon or a motion command to an arm, and a safety layer can veto

commands that would enter forbidden zones. Action executes the motion and returns feedback to the surgeon through the visual display or haptic channels.

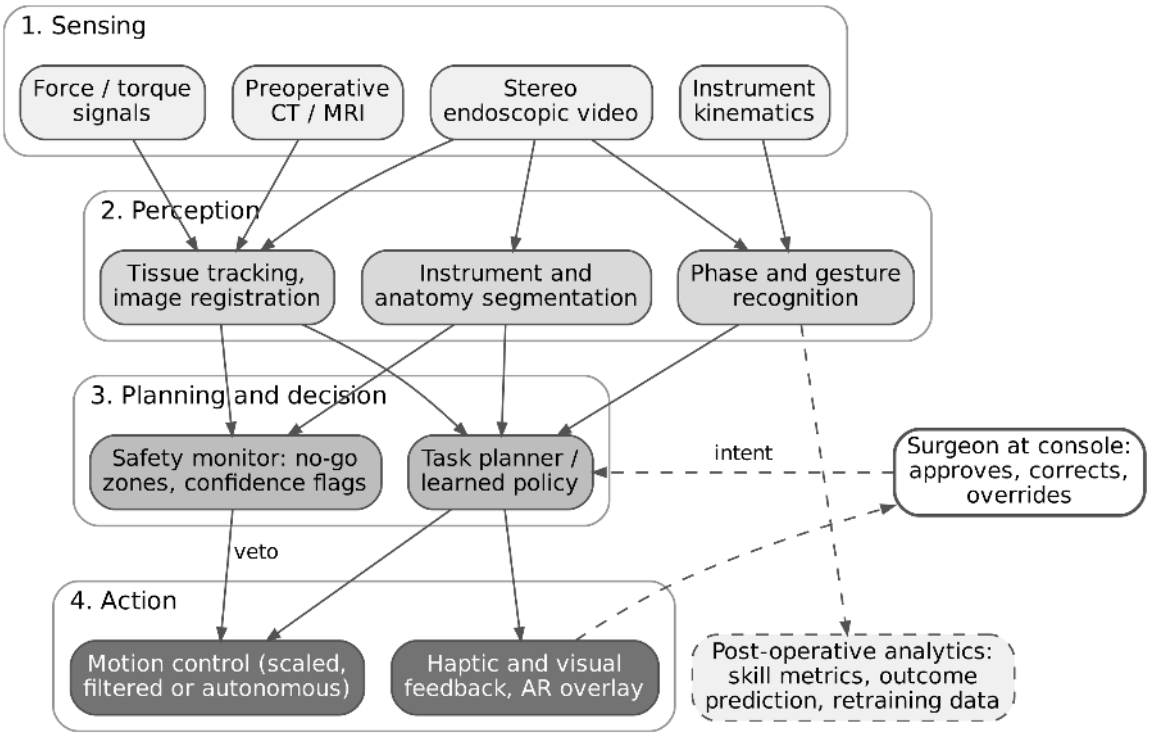

Figure 3.2: A perception, planning and action pipeline for AI-enabled robotic surgery. Solid arrows show intraoperative data flow; dashed arrows show supervisory and post-operative links. Original schematic synthesised from the surgical data science and autonomy literature [2,25,26].

Most current clinical value lies at the two ends of this pipeline. Sensing and post-operative analytics, which review finished cases for skill metrics and outcome prediction, can be deployed without changing how the robot moves. The middle stages, in which perception drives planning and planning drives action in real time, are where nearly all the regulatory and safety difficulty lies.

5.2 Computer vision: instruments and anatomy

The endoscopic image is the richest data source in minimally invasive surgery, and computer vision is the most mature AI component. Instrument detection and segmentation came first, because instruments are rigid, have known geometry and, on a robotic platform, have known kinematic positions that can be used to generate training labels. Sarikaya and colleagues applied deep neural networks for region proposal and detection to localise robotic tools in surgical video [28]. Shvets and colleagues applied deep convolutional segmentation networks to robotic instrument segmentation, separating instruments from the surrounding tissue at the

pixel level [29]. These tasks underpin almost everything else: tool tracking feeds skill assessment, collision avoidance, camera control and the counting of instrument usage.

Anatomy is harder. Soft tissue deforms, bleeds, is covered by fat and looks different in every patient. A segmentation error on an instrument is usually harmless; a segmentation error that labels the common bile duct as the cystic duct could contribute to the injury that safety checklists are designed to prevent. For this reason anatomy recognition models are increasingly evaluated against expert consensus annotation rather than single annotators, and claims about them should be read with attention to how ground truth was defined.

5.3 Surgical phase and step recognition

Recognising where an operation has reached is useful for scheduling, for automatic video indexing, for prompting safety checks at the right moment and as an input to more ambitious autonomy. The reference dataset in this area is **Cholec80**, released with the EndoNet architecture by Twinanda and colleagues [30]. It contains 80 laparoscopic cholecystectomy videos recorded by 13 surgeons at 25 frames per second, annotated with seven surgical phases and the presence of seven tools. EndoNet, a convolutional network trained jointly for tool presence and phase recognition, reported a mean average precision of 81.0% for tool presence; with a hierarchical hidden Markov model added for temporal smoothing it reached 92.0% phase-recognition accuracy offline and 81.7% online [30]. The gap between the offline and online figures matters more than either number. Offline recognition can use the whole video, including what happened next; a system that must help during surgery has only the past, and its accuracy falls accordingly.

Later work extended phase recognition to other procedures. Hashimoto and colleagues trained a computer vision model on 88 laparoscopic sleeve gastrectomy cases and reported a mean step-recognition accuracy of 82% on held-out video [31], and Khalid and colleagues evaluated deep learning models that identified surgical actions and measured performance [32]. Two limitations recur across this literature. Most datasets come from a small number of expert centres, so models may not transfer to different surgeons, case mixes or camera systems. And phases are defined differently by different groups, which makes direct comparison of reported accuracies unreliable.

5.4 Skill assessment and outcome prediction

The strongest clinical argument for analysing surgical performance came from outside robotics. In 2013, Birkmeyer and colleagues asked 20 bariatric surgeons to submit a video of a laparoscopic gastric bypass, which peers then rated for technical skill. Among 10,343 patients, those operated on by surgeons in the lowest skill group had a complication rate of 14.5%, against 5.2% for the highest group [33]. If skill varies this much, and matters this much, then objective and scalable measurement of skill is worth pursuing.

Robotic platforms make such measurement practical, because the robot records exactly what the instruments do. The **JIGSAWS** dataset, collected by Johns Hopkins University and Intuitive Surgical, became the benchmark for this work [34]. It contains kinematic and stereo video data from eight surgeons of varying experience, each performing five repetitions of three bench-top tasks (suturing, knot-tying and needle-passing) on a da Vinci system, with gesture labels and global skill ratings on a modified Objective Structured Assessment of Technical Skills scale. A large body of gesture-recognition and skill-classification work has been built on it, reviewed by van Amsterdam and colleagues [35]. JIGSAWS has the virtue of being public and the weakness of being small and artificial. Eight surgeons performing dry-lab tasks cannot represent the variability of real operations, and very high classification accuracies on it should not be read as evidence of clinical readiness.

The more clinically ambitious line of work is the automated performance metric (APM) programme led by Hung and colleagues. APMs are derived from the robot's system data, such as instrument travel, velocity, camera movement and energy use, recorded during real radical prostatectomies. In 2018 the group reported that machine learning applied to APMs could predict post-operative length of stay [36], and summarised the case for such metrics as a way of anticipating clinical outcomes [37]. A conference summary of the programme reported about 85% accuracy for predicting length of stay dichotomised at two days [38]. In 2019 the group trained a deep survival model on APMs and clinical features to predict urinary continence recovery in 100 patients. Its concordance index was 0.599, only modestly better than chance; in a historical cohort of 493 patients, those operated on by surgeons with better APM profiles had higher continence rates at 3 months (47.5% vs 36.7%) and 6 months (68.3% vs 59.2%) [39]. The article was the subject of a published correction in 2026, which readers using its figures should consult. Later work moved from kinematics to video. Ma and colleagues identified 34,323 individual surgical gestures in 80 nerve-sparing prostatectomies from two centres and found that gesture sequences predicted erectile function at one year with an area under the curve (AUC) of 0.77 in one surgical team, compared with 0.69 for traditional clinical features [40].

The pattern in these results deserves attention. Associations between measured technique and patient outcome are consistent and biologically plausible. The predictive performance of individual models is moderate, sample sizes are small, and most data come from a few high-volume centres. A C-index near 0.6 is a research finding, not a clinical tool. Table 3.2 brings together representative tasks, datasets and reported performance.

Table 3.2: Representative AI tasks in robotic and minimally invasive surgery, with datasets and reported performance

Task	Dataset or setting	Method	Reported performance	Main limitation
Phase recognition	Cholec80: 80 cholecystectomy videos, 13 surgeons, 7 phases [30]	EndoNet CNN with hierarchical HMM	Accuracy 92.0% offline, 81.7% online [30]	Single centre; online accuracy notably lower
Tool presence detection	Cholec80, 7 tools [30]	EndoNet CNN	Mean average precision 81.0% [30]	Presence only, not location
Gesture and skill classification	JIGSAWS: 8 surgeons, 3 bench-top tasks, 5 repetitions each [34]	Many, including recurrent and temporal convolutional networks [35]	Wide range; see review [35]	Small, dry-lab, single platform
Length of stay after prostatectomy	Robotic system data from radical prostatectomy [36]	Machine learning on automated performance metrics	About 85% accuracy for stay of two days or less, as summarised [38]	Single institution; dichotomised outcome
Urinary continence recovery	100 prostatectomy patients [39]	Deep survival model on metrics and clinical features	C-index 0.599 [39]	Modest discrimination; small cohort
Erectile function at one year	80 nerve-sparing prostatectomies, 34,323 gestures, two centres [40]	Gesture sequence modelling	AUC 0.77 vs 0.69 for clinical features (team 1) [40]	Small; performance varied between teams
Autonomous anastomosis	Phantom and 4 live pigs [41]	STAR with machine-vision tissue tracking	Suture-spacing coefficient of variation 26.36% vs 41.42% (robot-assisted) and 45.37% (laparoscopic) in phantoms [41]	Slower than human; very small in vivo sample
Autonomous clipping and cutting	8 ex vivo porcine gallbladders [42]	Hierarchical language-conditioned imitation learning (SRT-H)	100% success without human intervention [42]	Ex vivo; no bleeding, breathing or perfusion

5.5 Registration and augmented reality

Augmented reality (AR) in robotic surgery means overlaying information on the surgeon's view, typically a three-dimensional model of the patient's anatomy built from preoperative CT or MRI, so that hidden structures such as vessels or a tumour margin can be seen through the tissue surface. The robotic console is a natural place to do this, because the surgeon already looks at a digital image and the system knows the camera's position.

The technical difficulty is **registration**: aligning the preoperative model to the patient as the patient lies on the table. Registration is straightforward for bone, which explains why the earliest image-guided robots were neurosurgical and orthopaedic [6,8]. It is much harder for

soft tissue, which shifts with insufflation, positioning, respiration and the surgeon's own retraction. An overlay that is accurate at the start of a case can drift as the operation proceeds, and a surgeon who trusts it may be more endangered than one who has no overlay at all. One pragmatic workaround is to place trackable markers on the tissue itself. The STAR system, discussed in Section 6, used near-infrared fluorescent markers and a plenoptic three-dimensional camera to follow deforming bowel during autonomous suturing [43]. Clinical AR remains largely at the stage of feasibility series. The scoping review cited earlier found no intraoperative AI application in robotic surgery that had been evaluated in a clinical investigation in humans [4], and the absence of comparative trials of AR guidance should temper enthusiasm about it.

5.6 Haptics and force sensing

Surgeons operating through a classical master-slave robot lose the sense of touch. Experienced robotic surgeons learn to judge tension from visual cues such as tissue blanching and suture deformation, and much of the robotic learning curve consists of acquiring this visual substitute for touch. Restoring force information has therefore been a long-standing goal of robotic engineering, particularly for suturing, where excessive tension breaks fine sutures and insufficient tension leaves knots loose.

The da Vinci 5's force-feedback instruments bring this capability into a widely used commercial platform for the first time [12], and the SAGES review cited in Section 3 shows that the consequences are not entirely predictable [13]. From an AI perspective, force sensing matters for another reason. It adds a data channel that, combined with video and kinematics, could support learned models of tissue handling and safe force thresholds. Whether such models improve outcomes is, at present, an open question.

6. Autonomous Milestones: What They Show and What They Do Not

Three experiments are cited more than any others as evidence that autonomous soft-tissue surgery is possible. Each deserves to be read for what it actually did.

The **Smart Tissue Autonomous Robot (STAR)** was first reported in 2016 [43]. It combined a plenoptic three-dimensional and near-infrared fluorescent imaging system with an autonomous suturing algorithm, and performed suturing and intestinal anastomosis on deformable tissue in an open surgical setting. In ex vivo porcine tissue and in living pigs, its consistency of suture spacing, leak pressure, number of needle removals for mistakes and lumen reduction compared favourably with manual laparoscopy, clinically used robot-assisted surgery and expert open surgery [43]. The system was supervised, with surgeons able to intervene. It is best described as Level 2 task autonomy.

In 2022 the group published a laparoscopic version [41]. In phantom tests the coefficient of variation of suture spacing was 26.36% for STAR, against 41.42% for robot-assisted surgery and 45.37% for manual laparoscopy, and STAR hesitated less per stitch. It was also slower: about 55 minutes for the phantom anastomosis, against about 32 minutes for robot-assisted surgery. In vivo, STAR completed anastomoses in four pigs, with mean leak pressure of 0.69 psi and lumen patency of 88.75%, and placed 66.28% of stitches correctly on the first attempt; a single manually operated control animal was available for comparison [41]. These are proof-of-concept data. Four animals cannot establish safety, and the leak pressures were lower than in the single control.

The third milestone came in July 2025, when Kim and colleagues reported **SRT-H**, a hierarchical system trained by imitation learning from demonstrations and conditioned on natural-language instructions [42]. A high-level policy decides which step to perform next and issues an instruction, including corrective instructions that trigger recovery behaviour; a low-level policy executes it. Applied to the clipping and cutting phase of cholecystectomy, the system completed the procedure on eight unseen ex vivo gallbladders with a 100% success rate and no human intervention [42]. Press accounts described 17 distinct tasks within the procedure and about 18,000 recorded demonstrations used in training, including deliberate errors from which the robot learned to recover; the robot was slower than an expert human surgeon [44].

SRT-H is a genuine methodological advance. It shows that the architecture behind recent progress in general-purpose robot learning, in which large numbers of demonstrations train a policy that generalises across variation, can be applied to surgical manipulation. Its limits are equally clear. The tissue was ex vivo, so there was no perfusion, no bleeding, no respiratory movement and no adjacent organs at risk. Eight cases establish feasibility, not reliability. And the step that was automated, clipping and dividing the cystic duct and artery, is meaningful only after a human or a separate system has correctly identified those structures, which is precisely where bile duct injuries originate. Placing SRT-H at Level 3 in Figure 3.1 reflects its step-level decision-making; it does not imply clinical readiness.

Taken together, these milestones mark real progress over a decade, from supervised suturing in open surgery to learned, multi-step laparoscopic manipulation. They also confirm the finding of the scoping review: almost nothing has been tested in living patients [4].

7. Telesurgery: From Operation Lindbergh to Intercontinental Networks

Operation Lindbergh proved in 2001 that a surgeon could operate across an ocean [10]. It did not make telesurgery practical. The link was expensive and dedicated, signal delay was a concern, and the regulatory, licensing and liability questions of operating on a patient in another jurisdiction had no settled answer. Telesurgery returned to serious attention only when public

networks, particularly fifth-generation (5G) mobile and modern fibre, began to offer low and stable latency at reasonable cost.

Latency is the defining technical variable. Delay between a surgeon's hand movement and the visual result degrades precision, and above some threshold it makes surgery unsafe. Experimental studies have attempted to define the maximum acceptable communication delay and the limits of image compression for telesurgery [45,46], and network quality now has to be treated as part of the surgical system. Chinese groups have been particularly active. Ultra-remote robot-assisted laparoscopic surgery over 5G was reported in 2020 [47]. A dual-console study with the KangDuo robot recorded a mean latency of 271 ms (range 206 to 307 ms) during a remote pyeloplasty in a human patient over combined 5G and wired networks, with packet loss below 1% [48]. A preclinical study between Beijing and Sanya, about 3,000 km apart, carried out 108 animal operations at total latencies of 170 to 320 ms and found that operations could be completed with bandwidth as low as 1 to 5 Mbps [49]. Table 3.3 summarises representative reports.

Table 3.3: Representative telesurgery reports, distances and latencies

Report	Route and distance	Subjects and procedures	Platform	Reported latency	Outcome as reported
Marescaux et al. 2001 [10]	New York to Strasbourg (transatlantic)	One human cholecystectomy	ZEUS	Not stated in sources consulted	Completed
Fan et al. 2023 [48]	Remote, 5G plus wired network	One human pyeloplasty; porcine partial nephrectomy	KangDuo-01	Mean 271 ms (human); 130 ms (animal, wired)	Completed; packet loss below 1%
Patel et al. 2024 [50]	Orlando to Shanghai	5 pigs; 10 radical and 2 partial nephrectomies	MicroPort MedBot	Mean 296 ms	No complications or conversions
Wang et al. 2025 [49]	Beijing to Sanya, about 3,000 km	108 animal operations	Not specified in abstract	170 to 320 ms tested	Completed at 1 to 5 Mbps bandwidth
Aldousari et al. 2025 [51]	Shanghai to Kuwait City, 6,935 km	5 human cases (3 prostatectomies, 2 partial nephrectomies)	Not specified in sources consulted	Mean round-trip 166.6 ms	No complications; no local takeover
SS Innovations, January 2025 [52]	Gurugram to Jaipur, 286 km	Cardiac procedures, including beating-heart TECAB	SSI Mantra	35 to 40 ms	Completed
SS Innovations, March 2025 [19]	Gurugram to Bengaluru, about 2,000 km	One human atrial septal defect closure	SSI Mantra	Described as imperceptible; no figure given	Completed in 2 h 40 min

International collaborations have extended these distances. In early 2024, surgeons in Orlando performed 12 nephrectomies on five pigs in Shanghai, with a mean latency of 296 ms and no complications or conversions [50]. In 2025, a surgeon in Shanghai performed five human

operations, three radical prostatectomies and two partial nephrectomies, on patients in Kuwait City 6,935 km away; mean round-trip latency was 166.6 ms, no network failures occurred and the local surgeon never needed to take over [51]. An international multispecialty consensus statement on best practices in telesurgery was published in 2025, an early step towards common standards [53].

India has contributed a distinctive set of demonstrations using the SSI Mantra and its remote console. In June 2024, the company reported the country's first human soft-tissue telesurgery, a robotic cholecystectomy performed over about 5 km in Delhi [54], and the Rajiv Gandhi Cancer Institute performed India's first cancer telesurgery with the surgeon in Gurugram and the patient at the institute's Rohini facility [18]. In January 2025, cardiac procedures including internal mammary artery harvesting and beating-heart totally endoscopic coronary artery bypass were performed over 286 km between Gurugram and Jaipur, with reported latency of 35 to 40 ms [52]. In March 2025, an atrial septal defect was closed in a 35-year-old patient at a Bengaluru hospital by a surgeon in Gurugram, about 2,000 km away [19]. A June 2026 report described a left internal mammary artery takedown performed from Georgetown, Guyana, on a robot at IRCAD India in Indore, nearly 20,000 km away; the report did not state whether the subject was a human patient [23]. By April 2026 the company counted 170 telesurgeries in total [24].

These achievements need careful framing. Most Indian telesurgery reports so far are press releases or news accounts rather than peer-reviewed series, and latency figures are often described qualitatively. In the human telesurgeries reviewed here, a surgical team was present at the patient's side and able to take over [19,51]. The clinical case for telesurgery is strongest where a specialist is scarce and a local team is competent but less experienced, which describes much of rural India. Its operational risks, including network failure, cybersecurity, cross-jurisdictional licensing and the allocation of liability between remote and local surgeons, are not yet governed by any settled Indian framework.

8. Clinical Outcomes and Cost

Robotic surgery has spread faster than the evidence that it improves outcomes over laparoscopy. The best-known randomised trial makes the point. ROLARR randomised 471 patients undergoing rectal cancer resection to robotic-assisted or conventional laparoscopic surgery. Conversion to open laparotomy, the primary outcome, occurred in 8.1% of the robotic group and 12.2% of the laparoscopic group; the adjusted odds ratio of 0.61 (95% CI 0.31 to 1.21; P = .16) was not statistically significant [55]. An accompanying commentary noted several qualifications [56]. The sample size had been calculated on an expected conversion rate of 34% drawn from earlier laparoscopic trials, whereas actual laparoscopic conversion rates had since fallen, so the trial may have been underpowered. An apparent benefit in men was

based on small numbers. The cost analysis found robotic surgery more expensive by a mean of US$1,132 per case (95% CI 191 to 2,072) even though it excluded the purchase and maintenance of the robot itself. Surgeon experience varied, and a sensitivity analysis hinted at benefit when surgeons had performed more robotic cases [56].

Later trials have produced a more mixed picture. The Chinese multicentre REAL trial randomised 1,240 patients with middle or low rectal cancer and, in its short-term analysis, reported a lower rate of positive circumferential resection margin with robotic surgery (4.0% vs 7.2%; difference -3.2 percentage points, 95% CI -6.0 to -0.4) and fewer complications of Clavien-Dindo grade II or higher within 30 days (16.2% vs 23.1%) [57]. The Korean COLRAR trial, by contrast, was stopped early because of poor accrual after randomising 295 patients, and found no significant difference in the rate of complete total mesorectal excision (80.7% robotic vs 77.1% laparoscopic) or in postoperative complications [58]. A 2019 meta-analysis of 73 studies (6 randomised trials and 67 observational studies, 169,236 patients) found lower odds of conversion with robotic surgery (odds ratio 0.40) and operative times about 38 minutes longer, but its trial sequential analysis was inconclusive and the authors rated the overall evidence as low in quality [59]. In rectal cancer, then, the randomised evidence supports robotic surgery as a safe alternative to laparoscopy in experienced hands, with some trials suggesting better pathological and short-term outcomes and others finding none [55,57,58]. Long-term oncological results from the newer trials will be important.

Cost is the persistent counterweight. An editorial on ROLARR, citing the manufacturer's investor materials, gave the purchase cost of a robot as US$0.6 to 2.5 million with annual maintenance of US$80,000 to 170,000, in addition to per-case instrument costs [56]. In India, a 2021 report put the price of a da Vinci system at Rs 15 to 17 crore and that of the SSI Mantra at Rs 4 to 5 crore, with the developer claiming operating and maintenance costs about one-third of the imported system's, and estimated that a robotic operation added about Rs 1.5 lakh to the cost of conventional surgery [22]. These figures come from company statements and journalism rather than independent health-economic analysis, and they should be read in that light.

AI has an uncertain relationship with this cost problem. If AI-based skill analytics shorten learning curves or reduce complications, they could improve the value of the robot. If they add subscription costs and data infrastructure without measurable outcome gains, they will make an expensive technology more expensive.

9. Safety, Adverse Events and Liability

The most comprehensive analysis of real-world robotic surgery safety remains that of Alemzadeh and colleagues, who examined 14 years of reports to the FDA's Manufacturer and User Facility Device Experience (MAUDE) database [60]. Between 2000 and 2013 they

identified 10,624 adverse event reports, including 144 deaths, 1,391 patient injuries and 8,061 device malfunctions (Figure 3.3). Against more than 1.7 million robotic procedures performed in the United States in that period, reported events were uncommon. Their character, however, was instructive: 14.7% of reports involved broken or burnt instrument pieces falling into patients. Cardiothoracic and head and neck surgery had markedly higher rates of death than gynaecology, urology and general surgery, at 52.2 against 5.7 deaths per 100,000 procedures in 2007 to 2013 [60].

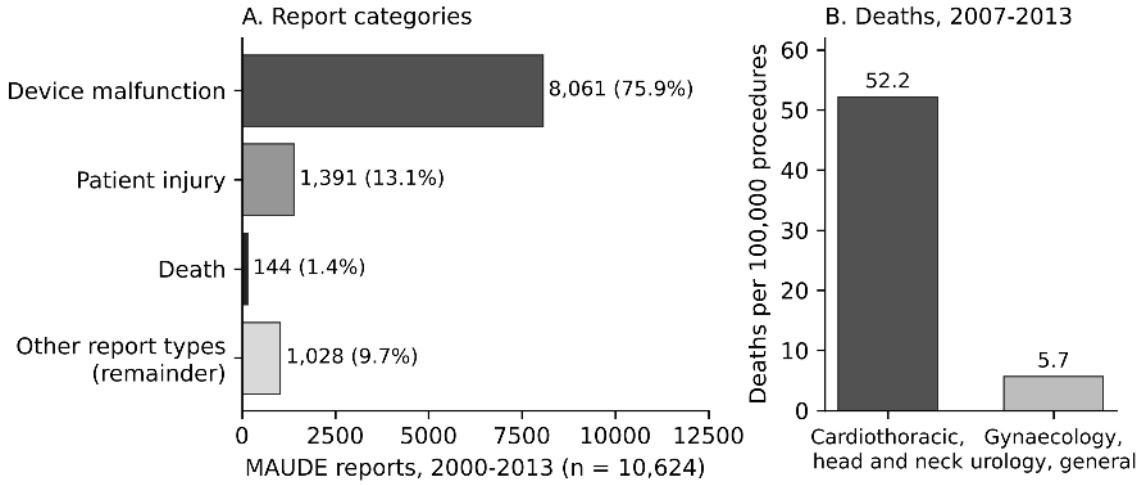

Figure 3.3: Adverse event reports for robotic surgical systems in the FDA MAUDE database, 2000 to 2013. (A) Report categories; the "other" bar is the remainder of the 10,624 reports after the three named categories. (B) Death rates per 100,000 procedures by specialty group, 2007 to 2013. Data from Alemzadeh et al. [60].

MAUDE data have well-known limits. Reporting is incomplete, causality is not established, and the denominator of procedures must be estimated from other sources. Under-reporting is likely. Even so, the analysis showed that a substantial share of harm arose from the machine itself rather than from surgical judgement, which points to a role for real-time monitoring of system behaviour. That is a natural use of AI: anomaly detection on kinematic and system logs, flagging an instrument or arm that behaves unexpectedly before harm occurs. Such safety-monitoring applications are less glamorous than autonomous suturing and arguably more useful.

Liability becomes more complex as autonomy rises. Under current practice the operating surgeon carries responsibility, the hospital is responsible for credentialing and maintenance, and the manufacturer is responsible for device defects. The autonomy framework makes explicit that once a robot chooses among strategies, responsibility for those choices must be shared with whoever designed the decision process, and that regulators will need evidence about the decision logic as well as the hardware [25]. Learned systems complicate matters

further, because their behaviour depends on training data and may change with updates. A model retrained on new video is, in a meaningful sense, a new device. For telesurgery, the questions multiply across jurisdictions, which is one reason expert groups have begun to codify best practice [53].

10. Training, Simulation and Credentialing

Robotic surgery has always relied heavily on simulation, because the console is a natural simulator: the same hand controls and display can drive a virtual environment. What AI adds is the possibility of automated, objective assessment within simulation and in real cases. A systematic review of performance measures in robotic surgery, covering studies published between 2020 and 2022, identified 72 eligible studies and 27 distinct metrics. Fifteen of these (58%) were subjective, global rating scales such as GEARS were the most frequently used tools, and automated performance metrics were the most widely used objective measures. The review found no standardised curriculum or performance measure across the field [61].

Machine learning applied to virtual reality simulation can separate expert from novice performance: in a neurosurgical tumour-resection simulator, a nearest-neighbour classifier using six performance metrics assigned 45 of 50 participants to the correct expertise group [62], and surgical data science has been proposed as a basis for more personalised surgical education [63]. Manufacturers have built training into their offerings; CMR Surgical, for example, describes a programme combining eLearning, virtual reality and preceptoring [14]. The unanswered question is whether automated metrics should be used for credentialing. Metrics that predict outcomes on average may be unfair to an individual surgeon whose case mix or technique differs from the training data, and a metric used for high-stakes decisions invites surgeons to optimise the metric rather than the operation. Automated assessment is best used for formative feedback until its validity across centres and populations has been established.

11. India: Adoption, Indigenous Technology and Barriers

India's experience with robotic surgery illustrates both the opportunity and the cost barrier. Adoption grew from a small base. A 2021 report counted 71 robotic installations across 66 centres as of July 2019 and more than 12,800 robot-assisted procedures over about twelve years, and cited a 2020 *Indian Journal of Urology* paper for a figure of more than 500 trained robotic surgeons [22]. For a population of over a billion, these numbers indicate access largely confined to private tertiary hospitals in major cities.

The SSI Mantra was conceived explicitly as a response to this gap. Its lower purchase price, local manufacture and service, and claimed lower running costs are aimed at hospitals that could not justify an imported system [22]. The published series from its early adopters,

reviewed in Section 3, show that the platform has been used across urology, gynaecology, general surgery and cardiac surgery with acceptable safety in experienced hands [20,21]. Its telesurgery programme adds a further argument: a single expert in Gurugram could, in principle, support teams in smaller cities, with the 2,000 km Bengaluru procedure as an example [19].

The barriers are not only financial. Robotic programmes need trained theatre teams, reliable maintenance, sterile processing for complex instruments and enough case volume to keep surgeons proficient. Telesurgery needs dependable, secure networks with low and predictable latency, which are uneven outside metropolitan areas. AI features add requirements for data storage, annotation and governance. Surgical video is identifiable health data, and the obligations that India's Digital Personal Data Protection Act 2023 places on such data, together with the federated approaches that allow models to be trained across hospitals without centralising it, are discussed in Chapter 8. Public insurance coverage of robotic procedures, and evidence on whether robotic surgery offers value in Indian health systems, remain thin; independent cost-effectiveness studies in Indian settings are a clear research priority.

12. Ethical Considerations

The ethical questions raised by AI in robotic surgery are mostly familiar ones applied to a new setting, but some are sharpened by the operating theatre.

Consent and disclosure. Patients consent to an operation by a named surgeon. When a robot will perform part of a procedure autonomously, or a remote surgeon will operate, patients need to understand who is doing what and what happens if the system or network fails.

Bias and generalisability. Models trained on video from a few high-volume Western or East Asian centres may perform differently on other patients, other surgeons and other equipment. Phase-recognition and skill models validated on one procedure in one or two institutions cannot be assumed to work elsewhere [30,39]. The same caution applies to skill metrics used to judge surgeons: a model that disadvantages surgeons who operate on more complex patients would be both unfair and harmful.

Surveillance and professional autonomy. Continuous recording of every movement creates a detailed record of each surgeon's performance. Used for feedback, it can improve care. Used for discipline or litigation without context, it could encourage defensive surgery and discourage surgeons from taking on difficult cases. Ownership of surgical video and robot data, between hospital, manufacturer, surgeon and patient, is not yet settled.

Deskilling. If assistance features become routine, surgeons may lose the ability to operate without them, exactly when a system fails. Training must preserve conventional skills, and safety designs must assume that the surgeon will need to take over.

Equity. The most expensive technology tends to reach the best-resourced patients first. A technology that improves outcomes modestly for urban private patients while absorbing funds that could expand basic surgical capacity elsewhere would be hard to justify ethically. The development of lower-cost platforms and telesurgery in India is, in part, an attempt to answer this objection, and it should be judged on whether it actually extends access.

Table 3.4 summarises the main challenges and the mitigations proposed in the literature.

Table 3.4: Principal challenges for AI-enhanced robotic surgery and proposed mitigations

Challenge	Evidence	Proposed mitigations
Almost no clinical evaluation of intraoperative AI	129 studies, all at IDEAL stage 0; 90% in silico or inorganic models [4]	Staged evaluation under the IDEAL framework; prospective clinical studies before autonomy claims
Small, single-centre datasets	Cholec80 from one centre [30]; JIGSAWS with 8 surgeons [34]	Multi-centre datasets; external validation; federated training (Chapter 8)
Modest predictive performance of outcome models	C-index 0.599 for continence [39]	Larger cohorts; combine video, kinematics and clinical data [40]
New features with unexpected harms	Force-feedback needle driver contraindicated after bleeding readmissions [13]	Feature-specific clinical evaluation; post-market surveillance
Device malfunctions	75.9% of MAUDE reports were malfunctions; 14.7% involved fragments falling into patients [60]	Real-time anomaly detection on system logs; mandatory reporting
Telesurgery network risk and jurisdiction	Latencies of 166 to 320 ms reported over long distances [49-51]	Redundant networks; local takeover team; consensus protocols [53]
Liability under autonomy	Responsibility shifts with autonomy level [25]	Explicit allocation of responsibility; regulation of decision logic and model updates
Cost and access	US$0.6 to 2.5 million purchase cost [56]; imported robot Rs 15 to 17 crore in India [22]	Lower-cost platforms; shared regional programmes; independent cost-effectiveness studies
No standard skill metric	27 metrics, 58% subjective [61]	Validated objective metrics; formative use before credentialing

13. Conclusion and Future Directions

Robotic surgery has passed through two eras and is entering a third. The first, from 1985 to the late 1990s, produced robots that positioned and milled with mechanical precision against rigid anatomy. The second, from 2000, produced teleoperated platforms that extended the surgeon's hands into the body without making decisions of their own. The third, now under way, adds a computational layer that perceives, measures and, in experimental settings, acts.

The evidence reviewed here supports a measured conclusion. AI has made substantial progress in perception: instruments can be segmented, phases recognised and gestures classified with useful accuracy on benchmark data. The association between measurable technique and patient outcome is real, and automated performance metrics and gesture analysis offer the first scalable

way to study it. Autonomous systems have progressed from supervised suturing in 2016 to learned multi-step manipulation in 2025, but have not been tested in living patients beyond a handful of animals. Telesurgery has become technically feasible over intercontinental distances, with Indian teams among those extending the record. In rectal cancer, the best-studied comparison, clinical outcomes have been at best modestly better than with laparoscopy, and costs remain high.

Several developments are likely to matter most in the coming years. Large, multi-centre, ethically governed video datasets, with consistent annotation of phases and anatomy, are the precondition for nearly everything else. Prospective clinical evaluation of intraoperative AI, following the IDEAL stages, should replace benchmark accuracy as the main measure of progress. Safety monitoring based on system logs and video, the least glamorous application, is the most likely to reduce harm in the near term. For India, the important questions are whether lower-cost indigenous platforms and telesurgery genuinely extend access beyond metropolitan private hospitals, and whether independent evidence on outcomes and cost will keep pace with deployment.

The surgeon will remain at the centre of the operating theatre for the foreseeable future. AI's most realistic near-term contribution is to make that surgeon better informed, better trained and better monitored, which is a more modest goal than autonomy and a more useful one.

REFERENCES

1. Sheetz KH, Claflin J, Dimick JB. Trends in the adoption of robotic surgery for common surgical procedures. JAMA Netw Open. 2020;3(1):e1918911. https://doi.org/10.1001/jamanetworkopen.2019.18911
2. Maier-Hein L, Vedula SS, Speidel S, Navab N, Kikinis R, Park A, et al. Surgical data science for next-generation interventions. Nat Biomed Eng. 2017;1(9):691-6. https://doi.org/10.1038/s41551-017-0132-7
3. Hashimoto DA, Rosman G, Rus D, Meireles OR. Artificial intelligence in surgery: promises and perils. Ann Surg. 2018;268:70-6. https://doi.org/10.1097/SLA.0000000000002693
4. Vasey B, Lippert KAN, Khan DZ, Ibrahim M, Koh CH, Layard Horsfall H, et al. Intraoperative applications of artificial intelligence in robotic surgery: a scoping review of current development stages and levels of autonomy. Ann Surg. 2023;278:896-903. https://doi.org/10.1097/SLA.0000000000005700
5. Rivero-Moreno Y, Echevarria S, Vidal-Valderrama C, et al. Robotic surgery: a comprehensive review of the literature and current trends. Cureus. 2023;15(7):e42370. https://doi.org/10.7759/cureus.42370
6. Kwoh YS, Hou J, Jonckheere EA, Hayati S. A robot with improved absolute positioning accuracy for CT guided stereotactic brain surgery. IEEE Trans Biomed Eng. 1988;35(2):153-60. https://doi.org/10.1109/10.1354

7. Paul HA, Bargar WL, Mittlestadt B, et al. Development of a surgical robot for cementless total hip arthroplasty. Clin Orthop Relat Res. 1992;(285):57-66.
8. Taylor RH, Mittelstadt BD, Paul HA, Hanson W, Kazanzides P, Zuhars JF, et al. An image-directed robotic system for precise orthopaedic surgery. IEEE Trans Robot Autom. 1994;10(3):261-75.
9. Bargar WL, Bauer A, Börner M. Primary and revision total hip replacement using the Robodoc system. Clin Orthop Relat Res. 1998;(354):82-91.
10. Marescaux J, Leroy J, Gagner M, Rubino F, Mutter D, Vix M, et al. Transatlantic robot-assisted telesurgery. Nature. 2001;413(6854):379-80. https://doi.org/10.1038/35096636
11. Marescaux J, Leroy J, Rubino F, Smith M, Vix M, et al. Transcontinental robot-assisted remote telesurgery: feasibility and potential applications. Ann Surg. 2002;235(4):487-92. https://doi.org/10.1097/00000658-200204000-00005
12. Intuitive Surgical. Intuitive announces FDA clearance of fifth-generation robotic system, da Vinci 5 [press release]. Sunnyvale (CA): Intuitive Surgical; 2024 Mar 14 [cited 2026 Nov 3]. Available from: https://investor.intuitivesurgical.com/news-releases/news-release-details/intuitive-announces-fda-clearance-fifth-generation-robotic
13. Benson J, Burstein MD. da Vinci 5 [device overview]. SAGES Technology and Value Assessment Committee (TAVAC) [Internet]. Society of American Gastrointestinal and Endoscopic Surgeons [cited 2026 Nov 3]. Available from: https://sages.org/publications/tavac/da-vinci-5
14. CMR Surgical. CMR Surgical receives U.S. FDA marketing authorization for next-generation Versius Surgical System [press release]. Cambridge (UK): CMR Surgical; 2024 Oct 15 [cited 2026 Nov 3]. Available from: https://www.biospace.com/press-releases/cmr-surgical-receives-u-s-fda-marketing-authorization-for-next-generation-versius-surgical-system
15. Medtronic. Medtronic announces FDA clearance of Hugo robotic-assisted surgery system for urologic surgical procedures [press release]. 2025 Dec 3 [cited 2026 Nov 3]. Available from: https://news.medtronic.com/2025-12-03-Medtronic-announces-FDA-clearance-of-Hugo-TM-robotic-assisted-surgery-system-for-urologic-surgical-procedures
16. Bianchi PP, Salaj A, Rocco B, et al. First worldwide report on Hugo RAS surgical platform in right and left colectomy. Updates Surg. 2023;75:775-80. https://doi.org/10.1007/s13304-023-01489-5
17. Dungy DS, Netravali NA. Active robotics for total hip arthroplasty. Am J Orthop (Belle Mead NJ). 2016;45(4):256-9.
18. Press Trust of India. Delhi's medical infrastructure can make it hub for less invasive robotic surgery: experts. ThePrint [Internet]. 2026 Sep 1 [cited 2026 Nov 3]. Available from: https://theprint.in/india/delhis-medical-infrastructure-can-make-it-hub-for-less-invasive-robotic-surgery-experts/3031147/
19. SS Innovations International Inc. Press release dated March 27, 2025: India's first north-to-south robotic cardiac telesurgery (Exhibit 99.1) [Internet]. Washington (DC): US Securities and Exchange Commission EDGAR; 2025 [cited 2026 Nov 3]. Available from: https://www.sec.gov/Archives/edgar/data/1676163/000101376225003006/ea023586101ex99-1_ssinno.htm

20. Rawal SK, Khanna A, Singh A, Pratihar SK, Malla I, Ali M, et al. Robotic uro-oncology applications of the SSI Mantra surgical robotic system. Asian J Urol. 2025;12(2):143-51. https://doi.org/10.1016/j.ajur.2024.04.009
21. Somashekhar SP, Sugara M, Agrawal K, Rawal SK, Singh A, Mehrotra M, et al. Real-world performance of the SSI Mantra robotic system: a multi-centric multi-specialty study evaluating its safety and surgical applications. J Robot Surg. 2026. https://doi.org/10.1007/s11701-025-03118-2
22. The Week. SSI's Mantra could bridge the disparity in access to robotic surgeries. The Week [Internet]. 2021 Jun 27 [cited 2026 Nov 3]. Available from: https://www.theweek.in/magazine/theweek/cover/2021/06/17/ssis-mantra-could-bridge-the-disparity-in-access-to-robotic-surgeries.amp.html
23. Indian Pharma Post. SS Innovations sets world record with longest-distance robotic cardiac telesurgery [Internet]. 2026 Jun 5 [cited 2026 Nov 3]. Available from: https://www.indianpharmapost.com/medical-device/lite/ss-innovations-sets-world-record-with-longest-distance-robotic-cardiac-telesurgery-20490
24. Surgical Robotics Technology. SS Innovations reaches over 10,500 surgeries with the SSi Mantra surgical robotic system [Internet]. 2026 [cited 2026 Nov 3]. Available from: https://www.surgicalroboticstechnology.com/news/ss-innovations-reaches-over-10500-surgeries-with-the-ssi-mantra-surgical-robotic-system/
25. Yang GZ, Cambias J, Cleary K, Daimler E, Drake J, Dupont PE, et al. Medical robotics: regulatory, ethical, and legal considerations for increasing levels of autonomy. Sci Robot. 2017;2:eaam8638. https://doi.org/10.1126/scirobotics.aam8638
26. Gumbs AA, Frigerio I, Spolverato G, Croner R, Illanes A, Chouillard E, et al. Artificial intelligence surgery: how do we get to autonomous actions in surgery? Sensors (Basel). 2021;21(16):5526. https://doi.org/10.3390/s21165526
27. Treat MR, Amory SE, Downey PE, Taliaferro DA. Initial clinical experience with a partly autonomous robotic surgical instrument server. Surg Endosc. 2006;20:1310-4. https://doi.org/10.1007/s00464-005-0511-0
28. Sarikaya D, Corso JJ, Guru KA. Detection and localization of robotic tools in robot-assisted surgery videos using deep neural networks for region proposal and detection. IEEE Trans Med Imaging. 2017;36:1542-9. https://doi.org/10.1109/TMI.2017.2665671
29. Shvets AA, Rakhlin A, Kalinin AA, Iglovikov VI. Automatic instrument segmentation in robot-assisted surgery using deep learning. In: Proceedings of the 17th IEEE International Conference on Machine Learning and Applications (ICMLA); 2018; Orlando, FL. p. 624-8.
30. Twinanda AP, Shehata S, Mutter D, Marescaux J, de Mathelin M, Padoy N. EndoNet: a deep architecture for recognition tasks on laparoscopic videos. IEEE Trans Med Imaging. 2017;36(1):86-97. https://doi.org/10.1109/TMI.2016.2593957
31. Hashimoto DA, Rosman G, Witkowski ER, Stafford C, Navarette-Welton AJ, Rattner DW, et al. Computer vision analysis of intraoperative video: automated recognition of operative steps in laparoscopic sleeve gastrectomy. Ann Surg. 2019;270(3):414-21. https://doi.org/10.1097/SLA.0000000000003460

32. Khalid S, Goldenberg M, Grantcharov T, Taati B, Rudzicz F. Evaluation of deep learning models for identifying surgical actions and measuring performance. JAMA Netw Open. 2020;3:e201664. https://doi.org/10.1001/jamanetworkopen.2020.1664
33. Birkmeyer JD, Finks JF, O'Reilly A, Oerline M, Carlin AM, Nunn AR, et al. Surgical skill and complication rates after bariatric surgery. N Engl J Med. 2013;369(15):1434-42. https://doi.org/10.1056/NEJMsa1300625
34. Gao Y, Vedula SS, Reiley CE, Ahmidi N, Varadarajan B, Lin HC, et al. JHU-ISI Gesture and Skill Assessment Working Set (JIGSAWS): a surgical activity dataset for human motion modeling. In: Modeling and Monitoring of Computer Assisted Interventions (M2CAI), MICCAI Workshop; 2014.
35. van Amsterdam B, Clarkson MJ, Stoyanov D. Gesture recognition in robotic surgery: a review. IEEE Trans Biomed Eng. 2021. https://doi.org/10.1109/TBME.2021.3054828
36. Hung AJ, Chen J, Che Z, et al. Utilizing machine learning and automated performance metrics to evaluate robot-assisted radical prostatectomy performance and predict outcomes. J Endourol. 2018;32(5):438-44.
37. Hung AJ, Chen J, Gill IS. Automated performance metrics and machine learning algorithms to measure surgeon performance and anticipate clinical outcomes in robotic surgery. JAMA Surg. 2018;153(8):770-1. https://doi.org/10.1001/jamasurg.2018.1512
38. UroToday. SIU 2021: The quantified surgeon: predicting patient outcomes after robotic surgery and automating skills assessment [Internet]. 2021 [cited 2026 Nov 3]. Available from: https://www.urotoday.com/conference-highlights/siu-2021/133939-siu-2021-the-quantified-surgeon-predicting-patient-outcomes-after-robotic-surgery-and-automating-skills-assessment.html
39. Hung AJ, Chen J, Ghodoussipour S, Oh PJ, Liu Z, Nguyen J, et al. Deep learning on automated performance metrics and clinical features to predict urinary continence recovery after robot-assisted radical prostatectomy. BJU Int. 2019;124(3):487-95. https://doi.org/10.1111/bju.14735
40. Ma R, Ramaswamy A, Xu J, Trinh L, Kiyasseh D, Chu TN, et al. Surgical gestures as a method to quantify surgical performance and predict patient outcomes. NPJ Digit Med. 2022;5(1):187. https://doi.org/10.1038/s41746-022-00738-y
41. Saeidi H, Opfermann JD, Kam M, Wei S, Leonard S, Hsieh MH, et al. Autonomous robotic laparoscopic surgery for intestinal anastomosis. Sci Robot. 2022;7(62):eabj2908. https://doi.org/10.1126/scirobotics.abj2908
42. Kim JW, Chen JT, Hansen P, Shi LX, Goldenberg A, Schmidgall S, et al. SRT-H: a hierarchical framework for autonomous surgery via language-conditioned imitation learning. Sci Robot. 2025;10(104):eadt5254. https://doi.org/10.1126/scirobotics.adt5254
43. Shademan A, Decker RS, Opfermann JD, Leonard S, Krieger A, Kim PCW. Supervised autonomous robotic soft tissue surgery. Sci Transl Med. 2016;8(337). https://doi.org/10.1126/scitranslmed.aad9398
44. AIwire. Robot surgeon executes key phase of surgery without human assistance. HPCwire [Internet]. 2025 Jul 9 [cited 2026 Nov 3]. Available from: https://www.hpcwire.com/aiwire/2025/07/09/robot-surgeon-executes-key-phase-of-surgery-without-human-assistance/

45. Nankaku A, Tokunaga M, Yonezawa H, et al. Maximum acceptable communication delay for the realization of telesurgery. PLoS One. 2022;17:e0274328. https://doi.org/10.1371/journal.pone.0274328

46. Takahashi Y, Hakamada K, Morohashi H, et al. Verification of delay time and image compression thresholds for telesurgery. Asian J Endosc Surg. 2023;16:255-61. https://doi.org/10.1111/ases.13150

47. Zheng J, Wang Y, Zhang J, et al. 5G ultra-remote robot-assisted laparoscopic surgery in China. Surg Endosc. 2020;34:5172-80. https://doi.org/10.1007/s00464-020-07584-5

48. Fan S, Xu W, Diao Y, Yang K, Dong J, Qin M, et al. Feasibility and safety of dual-console telesurgery with the KangDuo Surgical Robot-01 system using fifth-generation and wired networks: an animal experiment and clinical study. Eur Urol Open Sci. 2023;49:6-9.

49. Wang Y, Ai Q, Shi T, Gao Y, Jiang B, Zhao W, et al. Influence of network latency and bandwidth on robot-assisted laparoscopic telesurgery: a pre-clinical experiment. Chin Med J (Engl). 2025;138(3):325-31. https://doi.org/10.1097/CM9.0000000000003257

50. Patel V, Dohler M, Marescaux J, Saikali S, Gamal A, Reddy S, et al. Expanding surgical frontiers across the Pacific Ocean: insights from the first telesurgery procedures connecting Orlando with Shanghai in animal models. Eur Urol Open Sci. 2024;70:70-8. https://doi.org/10.1016/j.euros.2024.09.009

51. Aldousari S, Almarzouq A, Eltafahny A, Alhelal S, Wang J, Hassan A, et al. The path to global equity in surgical care: clinical and technical results of cross-border, ultra-long-distance, Asia to Middle East human telesurgery. Int Braz J Urol. 2025;51(6):e20250331. https://doi.org/10.1590/S1677-5538.IBJU.2025.0331

52. The Week. Made-in-India surgical robotic system SSI Mantra conducts two telesurgeries from 286km away. The Week [Internet]. 2025 Jan 13 [cited 2026 Nov 3]. Available from: https://www.theweek.in/news/health/2025/01/13/made-in-india-surgical-robotic-system-ssi-mantra-conducts-two-telesurgeries-from-286km-away.amp.html

53. Patel V, Collins JW, Marescaux J, Dohler M, Saikali S, Dasgupta P, et al. International multispecialty consensus statement and expert opinion of best practices in telesurgery. J Robot Surg. 2025;19(1):135. https://doi.org/10.1007/s11701-025-02298-1

54. DT Next. India-made surgical robotic system aces first human trial in telesurgery. DT Next [Internet]. 2024 Jun 13 [cited 2026 Nov 3]. Available from: https://www.dtnext.in/lifestyle/technology/india-made-surgical-robotic-system-aces-first-human-trial-in-telesurgery-790104

55. Jayne D, Pigazzi A, Marshall H, Croft J, Corrigan N, Copeland J, et al. Effect of robotic-assisted vs conventional laparoscopic surgery on risk of conversion to open laparotomy among patients undergoing resection for rectal cancer: the ROLARR randomized clinical trial. JAMA. 2017;318(16):1569-80. https://doi.org/10.1001/jama.2017.7219

56. Levic K, Bulut O. Robotic-assisted laparoscopic surgery in treatment of rectal cancer. Laparosc Surg. 2018;2. https://doi.org/10.21037/ls.2018.02.03

57. Feng Q, Yuan W, Li T, et al. Robotic versus laparoscopic surgery for middle and low rectal cancer (REAL): short-term outcomes of a multicentre randomised controlled trial. Lancet Gastroenterol Hepatol. 2022;7:991-1004. https://doi.org/10.1016/S2468-1253(22)00248-5

58. Park JS, Lee SM, Choi GS, Park SY, Kim HJ, Song SH, et al. Comparison of laparoscopic versus robot-assisted surgery for rectal cancers: the COLRAR randomized controlled trial. Ann Surg. 2023;278(1):31-8. https://doi.org/10.1097/SLA.0000000000005788

59. Ng KT, Tsia AKV, Chong VYL. Robotic versus conventional laparoscopic surgery for colorectal cancer: a systematic review and meta-analysis with trial sequential analysis. World J Surg. 2019;43(4):1146-61. https://doi.org/10.1007/s00268-018-04896-7

60. Alemzadeh H, Raman J, Leveson N, Kalbarczyk Z, Iyer RK. Adverse events in robotic surgery: a retrospective study of 14 years of FDA data. PLoS One. 2016;11(4):e0151470. https://doi.org/10.1371/journal.pone.0151470

61. El-Sayed C, Yiu A, Vaughan-Shaw PG, Todd J, Lin P, Kasmani Z, et al. Measures of performance and proficiency in robotic assisted surgery: a systematic review. J Robot Surg. 2024;18:16. https://doi.org/10.1007/s11701-024-01864-3

62. Winkler-Schwartz A, Yilmaz R, Mirchi N, Bissonnette V, Ledwos N, Siyar S, et al. Machine learning identification of surgical and operative factors associated with surgical expertise in virtual reality simulation. JAMA Netw Open. 2019;2(8):e198363. https://doi.org/10.1001/jamanetworkopen.2019.8363

63. Ward TM, Mascagni P, Madani A, Padoy N, Perretta S, Hashimoto DA. Surgical data science and artificial intelligence for surgical education. J Surg Oncol. 2021;124:221-30. https://doi.org/10.1002/jso.26496