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Precision in practice: Unraveling the impact of artificial intelligence (AI) on surgical advancements

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ABSTRACT

Background: AI can provide objective, quantitative data from the operative room to stakeholders to not-only ensure they present accurate and granular data to attendees, but also so they can perform detailed root-cause analysis to identify often opaque or overlooked intraoperative factors that may have impacted the clinical outcomes. This enables the surgical team members to recognize surgical errors and events both during surgery and retrospectively is important in promoting future prevention of such surgical errors. AI-enhanced robotics only have the potential to enable automation in surgery at varying levels of autonomy. One limitation that hospitals and health care systems highlight concerns about medico-legal issues that may arise from capturing and evaluating granular data sources. Other limitation that AI endangers the surgical ethics and affects the patients' privacy data so that the implications of fairness and taxonomy of algorithmic bias in AI system are important factors in the ethics of AI. The aim of the study is to explore and synthesize existing literature to elucidate the significance and impact of AI on surgical advancements, highlighting its value in improving surgical outcomes, techniques, and overall patient care. Conclusion: The use of AI in surgery is time saving, decrease surgical malpractice, enhance surgical outcomes for patients with accurate medical documentations and surgical research. However, incorporation of AI into surgery presents unique and challenging problems that necessitate novel regulation.

Keywords: *Artificial Intelligence, Robotic Surgery, Laparoscopic Surgery, Minimally-Invasive Surgery, Surgical training.*

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1. INTRODUCTION

Artificial Intelligence (AI) is defined as the ability of a machine to recreate, approximate, or otherwise simulate intelligent human actions in understanding and solving the problems [1]. The term Artificial Intelligence (AI) was officially coming out in 1956 at the Dartmouth Summer Research Project meeting [2]. Although AI as a term was not coined until 1956, it was a concept to as far back as 4000 BC, in having autonomous machines that mimic the humans by the ancient Pharaohs [3]. Despite the concerns related to its use [4]. The aim of AI is to solve and understand problems [5]. AI is a field that has been influenced by mathematics, computer science, psychology, neurobiology, linguistics, economics, and others. There were 3 pillars that led to AI advancement as we know it today [6]. The first is marked by the attempt to connect basic machinery to the philosophy of thinking as seen in works spanning from Leonardo da Vinci to Alan Turing-and the rise of numerical reasoning and computing. The second pillar is the establishment of a basic understanding of logical reasoning coupled with attempts to define a reasoning machine. The third surrounds the development of techniques to answer the question of how one can quantify reasoning [7]. With the large database in surgery, came the necessity of AI to store the database, improve the ability study the healthcare, and to deliver a personalized targeted medical solution [8]. Volume, variety and velocity are the 3 main problems in large data sets. Then comes the challenge in these big data after data collection, then processing, management and application [9]. The aim of the study is to explore and synthesize existing literature to elucidate the significance and impact of AI on surgical advancements, highlighting its value in improving surgical outcomes, techniques, and overall patient care.

2. RESEARCH METHODOLOGY:

The study is a review of literature in which the research strategy for relevant references involved comprehensive searches of databases such as PubMed, Google Scholar, and relevant academic journals. All outdated studies were excluded from the study.

3. DISCUSSION

The integration of Artificial Intelligence (AI) into surgical practice represents a profound shift in the approach to healthcare. While AI's roots trace back to the mid-20th century, its role in surgery is now becoming increasingly significant. This review highlights the various facets of AI applications in surgery, from preoperative risk assessment to intraoperative support, surgical coaching, and postoperative analysis. These developments promise enhanced precision, efficiency, and personalization in surgical procedures.

1- Artificial Intelligence is the simulation of Human Intelligence:

AI refers to the simulation of human intelligence processes by machines, typically computer systems. AI encompasses a broad range of techniques that enable machines to mimic cognitive functions such as learning, problem solving, perception, and decision-making. AI differs, in the symbolic quote written by Alan Turing, that "Instead of trying to produce a programme to simulate the adult mind, why not rather try to produce one, which simulates the child's? If this were then subjected to an appropriate course of education one would obtain the adult brain" [10]. This could be occurred by manufacture deep neural networks which are typically composed of multiple convolutional layers used to efficiently extract the information from a high-dimensional inputs, pooling layers to reduce dimensions, and fully connected layers to aggregate neuron activation into output values [11] (Figure 1).

2- Role of AI in Surgical Education:

Surgery is a complex task that involves both technical skills and decision-making skills. A systematic review of the incidence of adverse events during surgery is over 14%, 14% of these adverse events were either fatal or severe and only 5% are preventable [12]. This highlights the role of surgical experience in reducing the potentially avoidable harm to the patients' health. The three main roles of AI in surgical education is simulative training, intraoperative analysis and postoperative analysis [13]. Several scoring systems have been developed for assessment. For Example, the Objective Structured Assessment of Technical Skills (OSATS) is a widely used evaluation tool and has been extensively studied and validated for the manual grading of surgical skills in the operating room for different procedures [14]. The OSATS global rating scale is based on the cumulative performance score on 7 domains using a 5-point Likert scale: (1) respect for tissue, (2) time and motion, (3) instrument handling, (4) knowledge of instruments, (5) the flow of operation, (6) use of assistants, and (7) knowledge of the specific procedure. With-drawbacks are despite the maximum possible rating is 35, there is no validated score for minimum competencies. Rather, this score was used to compare performance among a group of trainee (eg. Novice vs experienced). In addition, it requires trained observers to monitor and evaluate trainee in their performance, either live or by video and in the manual assessment which is time-consuming and ultimately subjective [14]. Other scoring systems are The Global Operative Assessment of Laparoscopic Skills (GOALS), the Global Evaluative Assessment of Robotic Skills (GEARS), and the Global Assessment of Gastrointestinal Endoscopic Skills (GAGES). Despite the effectiveness of such scoring systems in surgical education, there are several limitations with manual assessment, namely cost and bias. The manual assessment can be very time consuming and expensive because it needs experts' supervision during the process [15]. In addition, these evaluations are, even with rater training, ultimately subjective, and the results from multiple surgeons need to be aggregated to provide a sense of performance [16]. In addition, collecting laparoscopic videos as well as patient privacy-related concerns have validating AI algorithms [17] (Figure 2). For example, cholec80 from Institute de Recherche center les Cancers de l'Appareil Digestif (IRCAD) in Strasbourg, France, contains 80 videos from laparoscopic cholecystectomy with labels for surgical tools and phases [18]. Smaller publicly available data sets are from the 2016 M2CAI tool detection and workflow recognition challenges [19- 41] (Table 1, 2).

AI is applicable to a wide range of tasks including:

Tracking surgical instruments by identifying the presence, location, or pose of the tools from still images, video streams, and kinematic data [42]. Organizing the videos or kinematic data into different phases, tasks/sub-tasks, and gestures and classifying the surgical parts [43]. Segmenting the surgical scene by localizing the anatomic structures, and surgical instruments and parts [44]. Rating based on the performance for short snippets of tasks or entire operation length using the standard criteria such as OSATS, GOALS and GEARS [45].

For robot-assisted surgeries, the availability of data from different sensors is crucial in designing an AI-based system. Finally, multitask learning strategies have been rising in popularity in order to take advantage of the correlation among different tasks and the large amount of information present in each surgical record. Thus, a model may consist of multiple fully supervised outputs, a combination of fully and self-supervised tasks, or multiple intermediate tasks [46].

3- AI Challenge in Automated Surgical Coaching (ASC)

Due to the limitations of AI in surgical training, a common term of 'Surgical Coaching' is gaining popularity and meets the needs of current limitations in surgical training and assessment as well as continuous professional development of practicing clinicians. For example, in surgery, the Wisconsin Surgical Coaching Program (WSCP) has been adopted by multiple groups, including the American Hernia Surgery Quality Collaborative (AHSQC) and the Michigan Bariatric Surgery Collaborative (MBSC) [47]. The following table shows the coach activities to assess the surgeons' skills, identifying progress milestones, and recommending practice plans [48] (Figure 3).

Limitations to surgical coaching include limited availability and time of the coaches, affecting both scheduling and frequency of coaching sessions. Automated surgical coaching (ASC) could alleviate some limitations via automated skill assessment, automated video indexing for quicker review, putting algorithms and individualized learning plans [49].

4- Role of AI in Preoperative Risk Assessment/Stratification:

5- Examples of AI-based stratification model:

A- Mortality Risk Prediction with Random Forest and Neural Network: RheSCORE

RheSCORE was created by the University of Sao Paulo Medical Center to predict mortality risk for candidates who require valve surgery. The team collected data prospectively from 2919 patients, from which they developed 13 different models. Using the AUC metric, the models were then compared to each other and to benchmark scoring systems that are based on linear models (ie, Bernstein-Parsonnet, EuroSCORE II). The top 2 performing models were neural network and random forest, with AUC values of 0.973 and 0.981, respectively. The neural network RheSCORE model had a sensitivity of 0.286 and a specificity of 0.994, whereas the random forest model had a sensitivity of 0.591 and a specificity of 1.0. Both models outperformed all the benchmark models, the top 2 of which are Bernstein-Parsonnet and EuroSCORE II, with AUC scores of 0.876 and 0.857, respectively [49]. Despite its great performance, the score produced by the RheSCORE risk calculator is uninterpretable in terms of the input variables (eg, age, left atrial size, high creatinine) because it is based on black box random forest models. *Random forest* is so named because of the many decision trees it comprises every individual decision tree can be thought of as an interpretable flow chart. For example, one of the decision trees might be trained on the age, ejection fraction, and left atrial size subset of the whole data set, whereas another might be trained only on age, pulmonary hypertension, and the presence of high creatinine. When presented with a new input (ie, a patient), each of the decision trees of the random forest makes a yes or no mortality prediction; the most popular prediction is selected as the final output of the random forest [50].

B- Anastomotic Leak Prediction with Kernel Methods

Innovative nonlinear models have also been developed to predict the risk of particular complications. Soguero-Ruiz et al used kernel methods to train a model on data combined from heterogeneous sources. They trained the classification model on data from 402 patients admitted for colorectal cancer surgery, 31 of whom developed anastomotic leak. Three types of predictor variables were used: free text, blood tests, and vital signs. Free text was extracted from all the available documentation related to inpatient and outpatient visits and was analyzed according to the presence or absence of certain words (eg, coloanal, air). Nine different blood tests were included, encompassing measures of blood chemistry and cell count. The model's performance greatly improved when the model was trained on all 3 data types simultaneously (median AUC all = 0.96) compared to when it was trained on each data type individually (median AUC text = 0.83, AUC blood = 0.74, AUC vitals = 0.65) [51].

C- Decision Tree Models

We have described risk prediction tools based on linear models, where the surgical risk estimate is interpretable in terms of the input variables at the expense of missing important nonlinear patterns in the data. We then discussed powerful black box models that sacrifice interpretability but efficiently capture nonlinear patterns in a large data set and provide more accurate risk estimates than traditional prediction tools, namely, neural networks, random forest models, and nonlinear kernel methods. In the discussion of random forest models, we alluded to the fact that the output of an individual classification decision tree is fully interpretable in terms of the input variables. This is best demonstrated by walking through an example (Figure 4). Assume a surgeon wants to use a decision tree model to assess the mortality risk of a recently transfused non-septic patient whose leukocyte count is 8000. The only relevant variable at the first node of the tree is whether the patient received a transfusion in the past 72 hours. The right branch of the tree is followed to the next node, and the relevant variable at this node is whether the patient's preoperative leukocyte count is less than 15,510, which leads to the left branch of the tree. The most important variable at the next level is whether the patient is septic. Following the left branch of the tree again (because the patient is not septic), there are no further splits possible that would provide finer information about risk. The tree now makes a final mortality prediction of 71% (surgical intervention is very risky), and the decision tree model is transparent about why this is the case [51].

6- Role of AI in The OR (OR Black Box System) (OR BBS)

Similar to Warren's black box in aviation, the OR Black Box System (OR BBS) is a Canadian data-collecting platform to the whole intraoperative phase of surgery. The OR BBS simultaneously records audiovisual data, physiologic data from the patient, the whole surgical team, and the circulating team as well as the technical data from the instruments and sensors. Video and Audio data are captured from both the wide-angle room camera and the laparoscopic\robot camera [52]. During morbidity and mortality conferences, the OR BBS can provide objective, quantitative data from the OR to stakeholders to not-only ensure they present accurate and granular data to attendees, but also so they can perform detailed root-cause analysis to identify often opaque or overlooked intraoperative factors that may have impacted the clinical outcomes. This enables the surgical team members to recognize surgical errors and events both during surgery and retrospectively is important in promoting future prevention of such surgical errors [52]. For example, Generic Error Rating Tool (GERT) [53] (Figure 5). Only limitation that many hospitals and health care systems highlight concerns about medico-legal issues that may arise from capturing and evaluating these granular data sources [54].

7- Role of AI in Robotic Surgery:

AI and robotics can benefit surgery together and individually. Robots are cyper-physical systems that sense, think and act. These systems have both computational (software) and physical (hardware) components [55]. Not all robotics are AI systems. AI-enhanced robotics only have the potential to enable automation in surgery at varying levels of autonomy, including assistance (currently in use; example: STAR Robot), supervised/conditional autonomy (in prototype use), and full autonomy (in development) [56] (Figure 6). Autonomous knot tying combines computer vision to view the suture and interpret it and additional software to manipulate the suture to tie a knot using the robot. It requires tracking of effective suture length to keep constant tension on the suture because insufficient tension results in loose knots or open wounds and too much tension results in torn tissue. This can be simplified by an interrupted suture pattern, such that tightening can be accomplished by pulling 2 ends of suture in opposite directions parallel to the wound with uniform rate and tension. Running suture adds complexity because suture lengths are not the same on both sides, and as such, the rate and tension on each end are not the same. These problems have been described at length in the literature [57]. Knoll et al and Osa et al both used a concept of learning by demonstration, where the computer analyzes a library of knot-tying movements and then breaks down each trajectory into a sequence of temporally non-overlapping steps [57, 58]. Osa et al were able to execute knot tying even when moving the target for suturing and when changing the stiffness of the surface by rapid updating of the needle robotic arm trajectory. Many reports on this subject do not report the time to execute a task [58]; in Lu et al, creating one loop of suture took an average of 408 seconds (6.8 minutes). Autonomous suturing tests of the robot performing 4 running suture throw-and-throw were attempted with a 50% failure rate due to incorrect needle re-grasp and pull. Future applications of AI could include virtual assistance and mentors, improved situational awareness, and an interface to a collective surgical consciousness [59].

8- Role of AI in Medical Documentation and Research:

Natural Language Processing (NLP) is collection of tools and computer algorithmic techniques that aim to help human's structure and gain in-depth understanding of free text information [60]. NLP is a subfield of AI and ML that concentrates on the capture, interpretation, and manipulation of human-spoken data (examples: Google Maps or Apple Siri) or written data (examples: Gmail or Microsoft Outlook). Currently, most of the data in electronic health records reside in free-text documentation, often unstructured, useless for AI without preprocessing. NLP plays the dual function of unlocking meaning from free-text and unstructured documentation and improving the creation of clinical documentation in the healthcare facility [61].

The advantage of NLP use cases includes data mining research, computer-assisted coding, automated registry reporting, clinical trial matching, prior authorization, clinical decision support, risk adjustment, hierarchical condition category (HCC) coding, computational phenotyping, biomarker discovery, and population surveillance. Challenges of the use NLP in healthcare are: the availability of unstructured or narrative or abbreviated or even missed clinical data, the need of permissions to use and consolidate these data, the lack of alignment within clinical organizations around how to prioritize the implementation and development of NLP [62].

9- AI is a double-edged scalpel: Ethical considerations of the use of AI in surgery

There are a standard four key principles of ethics/doctor's oath words in healthcare: (1) respect for patient autonomy, (2) non-maleficence, (3) beneficence, and (4) justice [63]. However, AI includes all the risks typically occurred in software bugs and hackers with lack of dependability. For Example, STAR robots have begun to perform in vivo and ex vivo surgical tasks in a quite controlled conditions. Moreover, they used to take a surgical decision prior to the surgery. In such circumstances, AI endangers the surgical ethics and affects the patients' privacy data. So the implications of fairness and taxonomy of algorithmic bias in AI system are important factors in the ethics of AI. That is why ethics in AI is dynamic and under continuous monitoring in surgery and under strict revisions for the sake of patient's safety [64]. Incorporation of AI into surgery presents unique and challenging problems that necessitate novel regulation. Regulations for surgical AI must focus on ensuring safety, efficacy, equity and privacy [65]. Beyond regulations, policy must adapt to clarify patient rights, malpractice liability, and adequate surgical training and competency maintenance [66].

4. CONCLUSION

The Use of AI in surgery is time saving, decrease surgical malpractice, enhance surgical outcomes for the patient with accurate medical documentations and surgical research. However, incorporation of AI into surgery presents unique and challenging problems that necessitate novel regulation. Regulations for surgical AI must focus on ensuring ethics, safety, efficacy, equity and privacy. Beyond regulations, policy must adapt to clarify patient rights, malpractice liability, and adequate surgical training and competency maintenance.

Declarations

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Table 1: Summary of the most important papers for AI-based analysis of laparoscopic surgeries using recorded videos MICCAI 2015: Endovis 2015 Instrument Segmentation and Tracking. Accessed September 30, 2020, https://endovissub-instrument. grand-challenge.org.
3D: 3-dimensional Al: Artificial intelligence CNN: Convolutional neural network GOALS: Global Operative Assessment of Laparoscopic Skills LSTM: Long short-term memory RNN: Recurrent neural network SPD:

Method	Year	Task	Data Set	Data	Highlights
TCN [31]	2016	Gesture Recognition	JIGSAWS	Kinematics Videos	Temporal considerations Network.
Liu and Jiang [32]	2018	Gesture Recognition	JIGSAWS	Kinematics Videos	Deep reinforcement Learning for handling Oversegmentation.
Sarikaya et al [33]	2018	Task recognition Gesture Recognition	JIGSAWS	Videos	Multitask learning, Multimodel (RGB+flow).
Sarikaya et al [34]	2019	Task recognition	JIGSAWS	Videos	Motion features Dense optical flow using CNN.
Zia et al [35]	2019	Phase detection	Radical Prostat-ectomy	Video	•CNN-LSTM for phase detection
Mohammed et al [36]	2019	Scene segmentation	EndoVis 2017	Video	Multiview segmentation, 2 encoders, 1 decoder
Da et al [37]	2019	Tool segmentation	STRAS robot	Video Kinematics	Self-supervised learning.
Du et al [38]	2018	Tool pose estimation	EndoVis 2017	Video	Multi-instrument parsing, Joint localization
FSNet [39]	2019	Tool pose estimation	EndoVis 2017	Video	Key points localization.
Fawaz et al [40]	2019	Skill assessment	JIGSAWS	Kinematics	Multitask learning.
Oğul et al [41]	2019	Skill assessment	JIGSAWS	Kinematics	2-stream network (Siamese).

Surgical phase detection.

Table 2: Summary of the most important papers for AI-based analysis of Robot- Assisted Surgeries

Method	Year	Task	Data Set	Highlights
Endo Net [19]	2017	Phase detection Tool detection	Cholec80	First deep-learning framework, Multitask learning.
Jin et al [20]	2018	Phase detection	Cholec80	End-to-end CNN-RNN training.
SPD [21]	2018	Phase detection	Cholec80	Timestamping frames, Long-term LSTM training.
Yi and Jiang [22]	2019	Phase detection	Cholec80 M2CAI16	Considering hard frames.
Bodenstedt et al [23]	2019	Phase detection Tool detection	Cholec80	Active learning.
Namazi et al [24]	2019	Phase boundaries	Cholec80	Sequence to sequence modeling, Attention mechanism.
Yengera et al [25]	2018	Phase detection Remaining time	Cholecl 20	Self-supervised learning.
Mishra et al [26]	2017	Tool detection	M2CAI16	End-to-end CNN-RNN training.
Al Hajj et al [27]	2018	Tool detection	Cholec80	Gradient boosting, Ensemble learning.
Jin et al [28]	2018	Tool detection Skill assessment	M2CAI16	Localizing tools with bounding boxes, GOALS assessment.
Nwoye et al [29]	2019	Tool localization Tool tracking	Cholec80	Weakly supervised learning, Temporal considerations.
MTRCNet-CL [30]	2020	Tool detection Phase detection	Cholec80	Multitask learning, Correlation-aware loss function.

AI: artificial intelligence CNN: convolutional neural network JIGSAWS: Gesture and Skill Assessment Working Set LSTM: long short-term memory; MISTIC-SL: Minimally Invasive Surgical Training and Innovation Center-Science of Learning RGB: red, green, and blue RNN: recurrent neural network TCN: Temporal convolutional network.

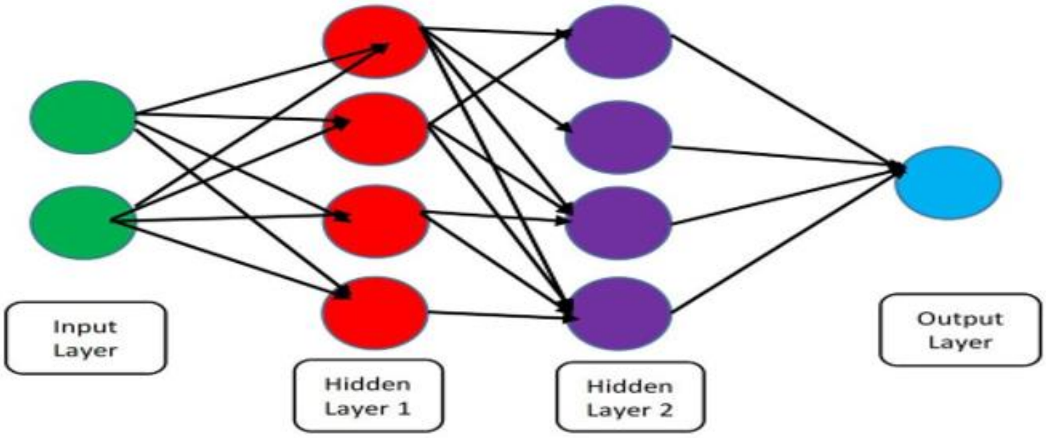

Figure 1 : Example of a neural network

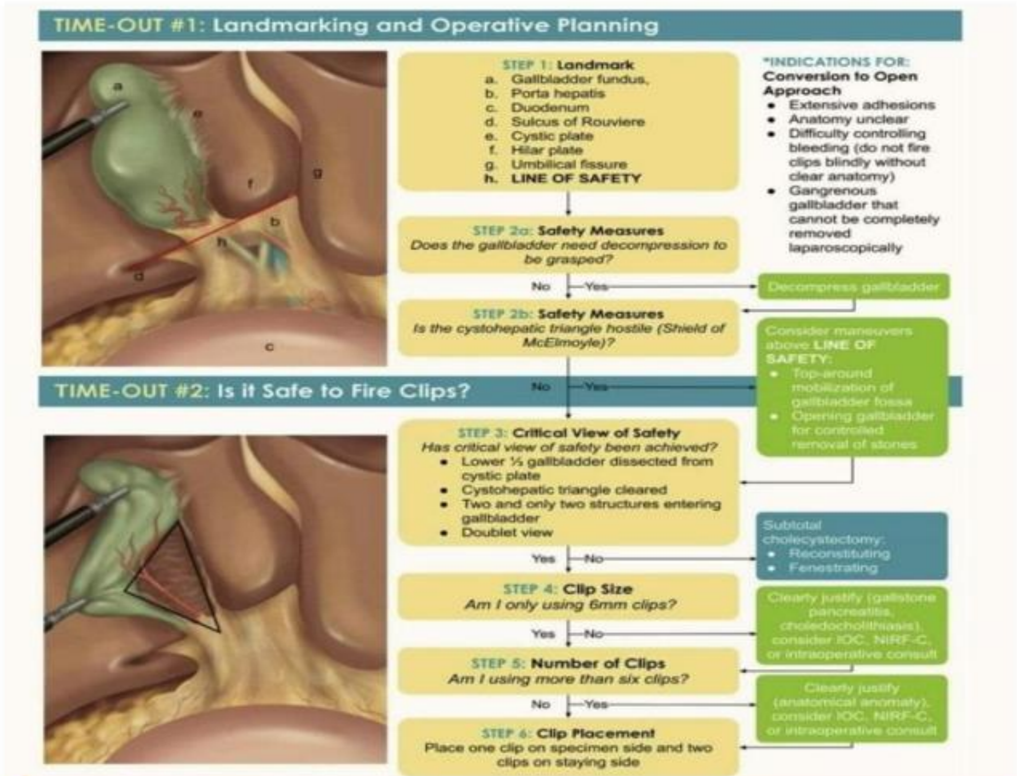

Figure 2: Algorithm for step-by-step approach for laparoscopic cholecystectomy. (1) Landmarking and operative planning, (2) Is it safe to fire clips?
IOC: Intraoperative Cholangiography, NIRF-C: Near-InfraRed Fluorescent Cholangiography

Figure 3 : Modified schematic of the Wisconsin Surgical Coaching Program (WSCP) framework

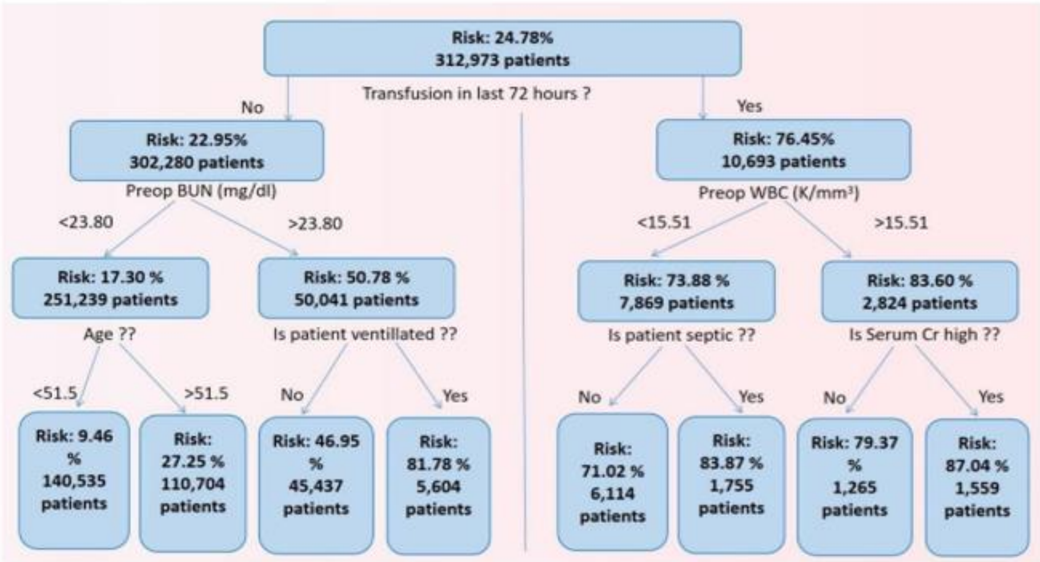

Figure 4: An illustrative example of a segment of a decision- tree to predict any complication (including mortality). SIRS, systemic inflammatory response syndrome. (Reproduced, with permission, from Bertsimas D, Dunn J, Velmahos GC, Kaafarani HMA. Surgical risk is not linear: derivation and validation of a novel, user-friendly, and machine-learning-based Predictive OpTimal Trees in Emergency Surgery Risk (POTTER) Calculator. Ann Surg. 2018;268(4):574-583.

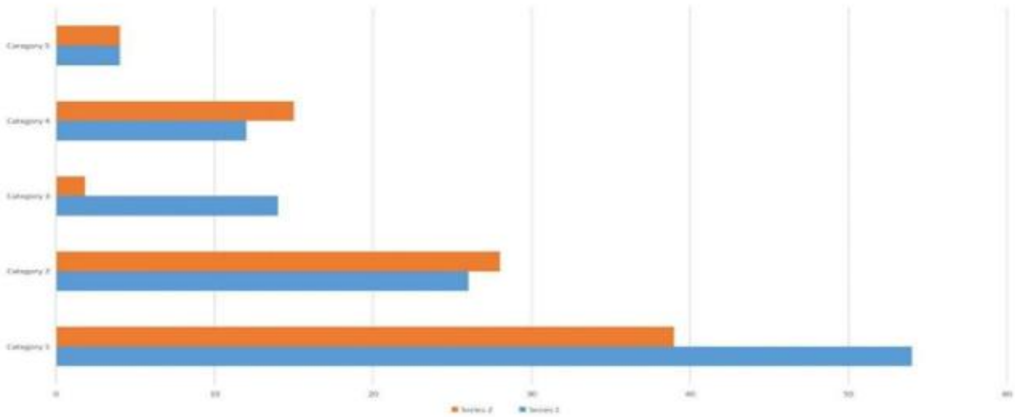

Figure 5: Characterizations of DRI in minimally-invasive surgeries

Figure 5: Characterizations of Device-related Interruptions (DRI) In minimally invasive surgeries ; According Surgical Safety Technologies Inc. © 2019. [34]
Blue columns shows DRI-Interruption which varies from category 1-5 into: device faliure, Improper assembly, Disconnection, Absent/Wrong device, and Unsterile Instrument in order. Orange columns shows DRI-Device which varies from category 1-5 into: Staplers, Visual, Monopolar, Others, and Suction/Irrigation in order.

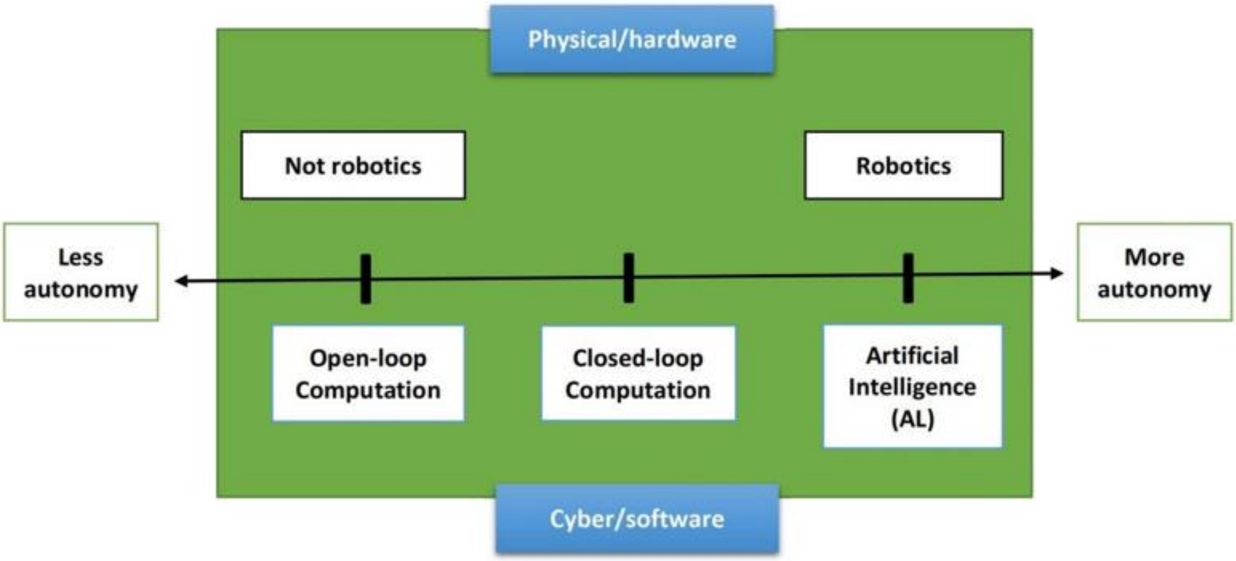

Figure 6: Spectrum of computation and hardware in automation.