Artificial Intelligence for Emerging Technology in Surgery: Systematic Review and Validation

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***Abstract* — Surgery is a high-risk procedure of therapy and is associated to post trauma complications of longer hospital stay, estimated blood loss and long duration of surgeries. Reports have suggested that over 2.5% patients die during and post operation. This paper is aimed at systematic review of previous research on artificial intelligence (AI) in surgery, analyzing their results with suitable software to validate their research by obtaining same or contrary results. Six published research articles have been reviewed across three continents. These articles have been re-validated using software including SPSS and MedCalc to obtain the statistical features such as the mean, standard deviation, significant level, and standard error. From the significant values, the experiments are then classified according to the null (p<0.05) or alternative (p>0.05) hypotheses. The results obtained from the analysis have suggested significant difference in operating time, docking time, staging time, and estimated blood loss but show no significant difference in length of hospital stay, recovery time and lymph nodes harvested between robotic assisted surgery using AI and normal conventional surgery. From the evaluations, this research suggests that AI-assisted surgery improves over the conventional surgery as safer and more efficient system of surgery with minimal or no complications.**

***Index Terms* —Surgery, artificial intelligence, robotic-assisted surgery, systematic review, and docking time**

I. Introduction

SURGERY is a branch of medicine that is associated with the manual administration of therapy to injuries, diseases and other medical disorder using instruments. The history of surgery has been back dated to the origin of man, which involves stanching of wounds. Surgery has been a therapy of high risk before the invention of modern technologies. Modern day surgery has been able to decrease the high risk involved in surgery through the emergence of high optimized technologies [1]. Artificial intelligence (AI) is a programmed simulation of human intelligence that mimics human actions such as learning, reasoning and perception. AI is the intelligence of both machine and electronics. Robot simply acts as an active agent whose environment is the physical world. A robot may not injure a human being, or through in action, allow a human being to come to harm [3]. The goal of the AI technology is to design programs that can make their own decisions and carry out the desired task with better efficiency and fewer errors in medicine [3]. The application of AI in surgery has played a key to reduce death rate association to complications resulting from surgical surround, instrument, and procedures [4]. The application of intelligent robotics is the most influential achievement of the 20th century [5]. The earliest robots named "Unimate" were invented and patented in 1950s [6]. And now, the intelligent robots can use tools, understand languages, help nurse elderly people, and even perform difficult tasks that cannot be done by human [7]. It took about twenty years for the robot to learn to walk with two legs from the crawl and become an upright robot while humans spent millions of years crawling to erect. As early as 1985, neurosurgeon performed a stereoscopic proceed with the assistance of a factory robot [8]. This was the first time that robotic technology is combined with surgeries, which subsequently led to the advances of AI robotics in medicine. After decades of rapid development, medical robots have gained pervasive acceptance in many areas. In neurosurgery, the robots are mainly deployed for precise positioning of brain lesions and for assisting doctors in holding and fixing surgical instruments [9]. Laparoscopic robots are used to perform minimally invasive laparoscopic procedures [10] related to cardiac surgery, urology, thoracic surgery, hepatobiliary and pancreatic surgery, gastrointestinal surgery, gynecology, and the like [11,12]. The development of AI robots is a vital part of artificial surgery in surgery and was an inspiration from the drawing book of Leonardo Da Vinci, which is the first surgical robot was named after him [13]. The application of AI in surgery poses a great advantage over the normal conventional surgery [14]. Some of the AI-based robotic surgery advantages over conventional system of surgery include:

- AI has improved the recovery time of patients to normal time
- AI has recorded success in treating patients with minimal incisions, less pain, less bleeding and reduced risk of infections
- AI in medicine allows for unprecedented control and precision of surgical instruments in minimally invasive procedures [15]

A. *Robotically Assisted Surgery*

The traditional and conventional methods of carrying out surgeries have led to many complications during surgery that have caused the deaths of many patients caused maybe by incompetence in surgeons or complexity of the illness. Most often, there has been an increased number of hospital stays or visitations and more severe issues after traditional surgeries. However, in robotic assisted surgery, a patient would experience minimal incision, better precision, less dependent of pain killer, minimal blood loss and blood transfusion, and reduced risk of infections after surgery [16]. There have also been successful surgery cases. In orthopedic surgery, the precision of the conventional handheld broach method coring

Table 1: Summary of the result [86]

BPE	(a) in-vivo kidney 1			(b) in-vivo kidney 2			(c) in-vivo uterus			(d) chicken thigh			(e) ex-vivo kidney		
	R2D2	R2D2-d	R-HMA	R2D2	R2D2-d	R-HMA	R2D2	R2D2-d	R-HMA	R2D2	R2D2-d	R-HMA	R2D2	R2D2-d	R-HMA
MED	1.37	1.33	2.67	1.67	4.96	3.8	4.71	5.19	28.99	2.69	3.16	5.19	1	2.03	4.18
IQR	1.67	1.69	6.34	2.6	6.44	10.53	6.77	6.73	55.13	2.93	4.04	8.5	1.37	2.45	14.28
mean	1.62	163	16.34	2.69	6.29	16.6	6.96	7.87	45.71	3.26	4.34	8.87	1.2	3.35	16.18
S.D	1.18	1.37	40.28	3.3	5.73	38.62	8.35	10	43.18	2.59	3.98	10.67	0.97	4.41	26.78
Max	9.71	8.98	261.74	30.2	36.49	264.76	61.1	77.67	210.32	21.4	33.61	94.58	8.49	31.75	159.43

CPE	(a) in-vivo kidney 1			(b) in-vivo kidney 2			(c) in-vivo uterus			(d) chicken thigh			(e) ex-vivo kidney		
MED	2.41	2.51	3.61	2.03	2.22	3.01	4.64	4.69	14.56	1.55	1.59	5.21	1.14	2.89	3.73
IQR	2.23	2.4	4.27	2.06	2.16	4.03	4.29	4.42	144.67	1.46	1.52	8.63	1.06	3.24	19.99
mean	2.94	3.09	11.98	2.49	2.52	9.08	7.21	6.85	288.83	1.81	1.96	9.5	1.39	3.48	15.67
S.D	2.36	2.48	2716	2.26	1.67	22.81	8.56	8.45	1100.4	1.22	1.64	12.84	1.06	2.76	31.01
Max	16.9	18.75	169.57	22.3	9.61	203.52	42.7	42.71	9780	7.82	16.61	86.29	6.48	21.44	373.69

out the femur results in approximately 75% prosthesis to borne contact. However, with robotic surgery, this precision is increased to 96%. In cardiac surgery, Da Vinci cardio surgery is robotic cardiac surgery conducted through very little incisions in the chest, cut with robot manipulated tools and very small instruments. Cardio robotic surgery has been used for different hearth related procedures such as coronary artery bypass, valve surgery, cardiac tissue ablation, tumor removal and heart defect repair.

B. Adverse Events in Robotic Surgery

In the study carried out at the University of Illinois, 144 deaths, 1391 injuries and 8061 device malfunctions were recorded out of a total of about 1.7 million robotic procedures carried out between January 2000 and December 2013 [17]. In the healthcare systems, medical images happen to be one of the largest data sources [18]. Most of the medical decisions taken by clinicians depend on the analysis of these medical images [19]. Either radiologists or clinicians themselves take up the work of manually analyzing the images which itself is a time-consuming process. However, with the advent of AI and machine learning (ML) into the field, image analysis is up to 1,000 times faster than the manual method. Not only AI support makes analysis faster, but also processes the results of the scanning process to be more accurate and detail than traditional practices currently in use [16, 20, 21].

C. Ethics on AI in Surgery

The white house published guidance for the regulation of AI applications, and it contains the following principles, public trust in AI, public participation scientific integrity and information quality, risk assessment and management, benefits and cost, flexibility, fairness and non-discrimination, disclosure and transparency, safety and security, interagency coordination.

D. Litigations in use of AI in Surgery

In the case of adverse events, the manufacturer, distributor, and retailer of the product maybe liable, even if they were not negligent. If a doctor used all care in selecting the device, but still something went wrong, then that surgeon is likely to be subject to malpractice.

E. Need to embrace AI in Surgery

AI robotic surgery is a minimally invasive surgery with minimal incision and faster recovery time compared to conventional surgery which gives rise to infections and longer recovery time. Also, AI robotic surgery allows unprecedented control and precision of surgical instruments in procedures and may not injure a patient.

F. Methodology used in AI in Surgery

Speech recognition is used to convert and transform human speech into a useful and comprehensive format. Machine learning (ML) is a sub-discipline of computer science as well as an important branch of AI. It develops new techniques enabling computers to learn and become intelligent. With the help of algorithms, application programming interface, training tools, big data and applications. Virtual agent is a program capable of interacting effectively with humans. Decision management uses artificial intelligent machines have the capability of introducing logic to AI systems in order to gear up to be used for training, maintenance and tuning. Deep learning is a form of machine learning that duplicates the neural circuits of the human brain to process data and create patterns for decision making. Algorithms use artificial neural networks, its applications are speech recognition, image recognition and prediction, in robotic surgery, the methodology involves centralized algorithm in which a single computer makes decisions for the whole team and decentralized algorithm in which each robot makes its own decisions based on local observations.

G. AI for Pre-Operative Planning

In preoperative planning, surgeons plan the surgical procedure using medical records and imaging. Routine tasks include anatomical classification, detection, segmentation, and registration [23]. In anatomical classification, the output is the diagnostic value of a set of medical images of organs or lesions. Khosravi et al. [24] proposed an architecture with a Convolutional Neural Network (CNN) of Google's Inception, with Inception and ResNet algorithm to segment the lung, bladder, and breast cancer types. Chilamkurthy et al. [25] proposed similar architecture to recognize intracranial haemorrhage. ResNet-50 [26] and Darknet-19 [27] have been used to classify benign or malignant lesions in ultrasound images. In detection, the task is to provide spatial localization of regions of interest to the surgeons. Rubinstein et al. [28] proposed a deeply stacked convolutional auto encoder to extract the statistical and kinetic biological features from 4D Positron-Emission Tomography images. 3D-CNNs with roto-translation group convolutions were proposed for pulmonary nodule detection [29], cartilage lesion detection [30], breast lesion detection [31], acute intracranial hemorrhage from CT scans [32]. In segmentation, the task is treated as a pixel- or voxel-level image classification problem where each image or volume was divided into small windows. AI algorithms are trained to predict the target label at the central location of the window. Encoder-decoder network such as U-Net [33, 34] has shown promising performances. CNNs are used for navigating the endoscopic pancreatic and biliary procedures [34,35], interactive segmentation of placenta and fetal brains [36], aortic MRI [37], segmentation and localization of surgical instrument landmarks [38] and labelling of vertebrae [39]. In image registration, the task is the spatial alignment between two medical images, volumes or modalities. 3D-CNNs are used for registering pulmonary CT images [40], anatomical labels [41], 3D volume to 2D X-ray images [42], and predicting deformation from image appearance [43]. In intra-operative guidance, AI has been utilized to provide enhanced visualization and localization in surgery. 3D prostate shape was instantiated from multiple 2D ultrasound images [44], and a similar strategy with 3D shape of abdominal aortic aneurysm using two 2D fluoroscopic images [45]. In addition, depth estimation using camera motion estimation and 3D structural environment mapping have often been utilized with AI algorithms [46,47,48,49,50,51,52].

H. AI-based Surgical Robots and Simulators

With the development of AI, surgical robots can achieve superhuman performance [53,54]. JHU-ISI Gesture and Skill Assessment Working Set (JIGSAWS) dataset [55] is the first public benchmark dataset for surgical activity segmentation and recognition. A soft boundary modified Gath-Geva clustering was proposed for segmenting kinematic data [56], detecting and clustering transitions between linear dynamic regimes based on kinematic, sensory, and temporal similarity [57]. Other traditional AI models for surgical subtask recognition include Hidden Markov Model [55], Conditional Random Field [58], Linear Dynamic Systems [59], Dynamic Time Warping [60], Gaussian Mixture Model [61], Gaussian Process Regression [62], dynamics model [63], finite state machine [64], and recurrent neural network [65]. Reinforcement Learning (RL) [66,67] has been utilized to control soft tissue manipulation, cutting gauze tensioning, and tube insertion. To efficiently reduce the learning time, the RL algorithm is initialized with the learned policies from human expert demonstrations [68, 69].

Table 2: Clinicopathological and radiological data [87]

	Median (range
Age (years), *n*	46(33-59)
Body mass index (kg/m2)	28.5(18.5-35.1)
FIGO stage	
IIB	4(40%)
IIIB	4(40%)
IVA	1(10%)
Recurrent	1(10%)
Histopathological type	
Squamos cell carcinoma	9(90%)
Adenocarcima	1(10%)
Pelvic lymph node metastasis by PET/CT	
Negative	3(30%)
Positive	7(70%)
Para-aortic lymph lymph node metastasis by PET/CT	
Negative	9(90%)
Positive	0%
Suspected	1(10%)
Tumor diameter(mm) by MRI	49(25-65)
Number of pelvic nodes retrieved	25.5(1-51)
Positive para-aortic nodes, proven with	5.5(2-11)
Number of para-aortic nodes retrieved	25.5(2-11)
Positive para-aortic nodes, proven with	291-5)
Hospital stays (days)	4(4-9)
Interval of radiotherapy(days)	12(6-23)

The deployment of AI techniques to identify components of expertise are required for the understanding and teaching of complex tasks [70]. Virtual reality surgical simulators can generate large amounts of data from each individual's specific operative performance [71,72,73] this data can be analyzed and filtered to quantify performance and provide automated feedback to the operators [74]. A number of virtual reality surgical training simulator platforms exist include the NeuroVR [75] and SimOrtho [76]. In the context of surgery, the Objective Structured Assessment of Technical Skills (OSATS) tool is considered the gold standard [77]. This method has been shown to be valid and reliable for some surgical tasks [78]. Schwartz et al. [79] have developed best practices guidelines for utilizing AI in surgical simulation studies based on systematic literature search. It offers objective and automated feedback for the learner based on performance metrics from virtual reality simulators, allowing for an enhanced understanding for the critical components of expert performance. The AI-based robotic surgical system uses sensors [80,81,82]. They are usually computer-enhanced robotic systems consists of three components, including a three-dimensional view of the surgical field including depth of field, magnification, and high resolution. The Zeus technology system [80] has three remotely controlled robotic arms, allowing a single surgeon to manipulate the laparoscope and two laparoscopic surgical instruments simultaneously. A computer controller translates the surgeons' movement from the handles to the robotic arms. The Da Vinci Heart Surgery [13,81] is a robotically-assisted heart surgery is a type of minimally invasive heart surgery performed by a cardiac surgeon. The surgeon uses a specially-designed computer console to control surgical instruments on thin robotic arms. This technology allows surgeons to perform certain types of complex heart surgeries with smaller incisions and precise motion control, offering patients improved outcomes. Robotic myomectomy [82] was developed and embraced by surgeons based on success laparoscopy had already achieved.

I. *Validation*

AI has enabled accuracy and precision in healthcare delivery by reducing the ambiguity in surgery. The conventional method of surgery has recorded a very high rate of mortality as a result of inefficient or lack of well experienced surgeons in the health sectors and their inability to diagnose properly and render the best solutions when complications arise. Researchers have suggested that high mortality rate is associated to surgery [83]. Also, the World Health Organization (WHO) has report that over 2.5% of patients die during surgery and after surgery (WHO, 2011). This mortality rate is suggested to have been associated to the inexperience of the surgeon of less precision of technologies used [84]. This has also resulted to an increased hospitalization after surgery causing discomfort to patients after a long stay and perpetual visitation of patients to the hospitals after discharge has been appalling to the health sector accompanied with the spread of infections to patients during procedures [85]. This research is aimed at reviewing the works of other researchers on AI for emerging technology in surgery and validating their results and this could be achieved by:

- Reviewing published research on AI in surgery
- Validating of analysis using statistical analysis
- Correlating the different result and drawing a reference point

The significance of this study is to validate the previous works of AI in surgery and ensure that the data, materials and methods used by previous researchers are currently used to obtain the same result as attained previously and hence validating their works. In this review, the following questions will be answered to provide the hypothesis that AI has brought improvement to surgery techniques:

(i) Is there any impact of AI on emerging technology in surgery?
(ii) Is there any significant different between AI-robotic surgery and conventional surgery?
(iii) What are the benefits of robotic assisted surgery to conventional surgery?

H_0: No significant difference between the two procedures or no significant impact of AI on emerging technology in surgery (i.e., $p > 0.05$)

H_a: Significant difference between the two procedures or no significant impact of AI on emerging technology in surgery (i.e., $p < 0.05$)

This paper is organized as follows: Section II reviews the six articles published on AI in surgery and the quantitative statistics reported therein. This comprises articles in journals across Europe, USA and Asia. Section III validates the quantitative results reported in those articles using statistical analysis tools and software. The results of the re-analysis are then reported and discussed in Section IV. Finally, Section V draws the conclusion of the paper.

II. STATISTICAL REVIEW OF AI IN EMERGING TECHNOLOGIES FOR SURGERY

In this work, we will undertake a review of six articles that have reported on the use of AI for surgery across three continents in Europe, USA, and Asia using statistical software for the data analysis. The review is conducted across computer science, statistics, and medical sources to identify key concepts and techniques within AI that are driving innovation within surgery domain. Limitations and challenges of working with AI are also reviewed.

A. *Article #1 [86]*

The paper titled "Robust, Real-time, Dense and Deformable 3D Organ Tracking in Laparoscopic videos" by Collins et al. [86], in 2016. The research is aimed at solving a major problem encountered in computer-assisted surgery. This problem is to robustly track soft-tissue three-dimensional organ models in laparoscope videos in real-time and over long duration. The research was carried out by using three main models; the first is a geometric model of outer structure of the organ. The second model is a deformation model with a

Table 3: Surgical outcome [87]

	n=10 median (range min-max)
Operation time for para-aortic node dissection (min)	120 (60-165)
Estimated blood loss (ml)	12.5 (10-20)
PALND docking time (min)	6.5 (4-15)
Trocar time (min)	14.50 (5-45)
Conversion to laparotomy (%)	0

Table 4: Post-operative complications [87]

	n
Post operative complications	
Trocar-site infection	1/10 (10%)
Symptomatic lymphocyst	1/10 (10%)
Blood transfusion	0

transfer function $f(P;X_t):\Omega \rightarrow \mathbb{R}^3$ such models used in the work are tetrahedral finite element models, cage, and trilinear interpolation. The third model used is a texture model. The geometric model gives a close surface mesh of the outer surface of the organ, while the deformation model was used convert a three-dimensional point of the close surface mesh to the laparoscope's coordinate frame at a particular time. Also an internal energy function was incorporated inside the deformation model to obtain the associated energy for converting the organ, thereby modifying the tracking issue. The texture model was used to simulate the photometric appearance of the close surface mesh, when used in conjunction with texture map to simulate the surface appearance even to changes of illumination. Five experimental cases were used to test for optimal performance, these cases were subdivided into two in-vivo porcine kidney, an ex-vivo porcine kidney, an in-vivo human uterus, and an ex-vivo chicken lap used for laparoscope training. Four of the experimental models were carried out with computed tomography while one of it was carried out on magnetic resonance imaging, and the segmentation was carried out using MITK. In each of the experimental case, a monocular laparoscope video of the object when deformed was used. The duration of the videos is between 57 to 82 secs. The cases were tested on the model and it was observed different number of tetrahedral elements; 1591, 1757, 1591, 8618, and 10028 respectively. After running the statistics of the quantitative performance in pixels, errors are computed using a default image of 640 pixels. Table 1 shows the summarized result [86].

B. Article #2 [87]

The paper titled "Robot-assisted laparoscopic transperitoneal infrarenal lymphadenectomy in patients with locally advanced cervical cancer by single docking" was carried out by Gucer et al. [87] in 2018. The research was carried out from January 2012 to December 2014, involving twelve patients suffering from locally advanced cervical cancer. After filling consent forms, two decline while the remaining ten proceed. The patient bio-data were evaluated and these bio-data were age, body mass index, clinical stage according to FIGO classification, histopathologic type and grade, number of para-aortic lymph nodes retrieved, positive para-aortic nodes on final pathology, total operative time (skin incision-to-skin closure), trocar time, console time, docking time, estimated blood loss (EBL), duration of hospital stay, detection rate of PET/CT for pelvic/para-aortic nodes and tumor diameter in MRI. The remaining patient took 1 mCi per 10kg of 18F-fluorodeoxyglucose (18FDG) to enable them to be scanned on CT and their blood glucose level was measured. After 60-90minutes, the CT scan was taken and the anatomical and structural analysis. All patients that accepted the surgery were placed on robot-assisted laparoscopic transperitoneal para-aortic lymphadenectomy up to left renal vein with or without pelvic lymphadenectomy. Da Vinci surgical system with standard surgical technique was used to carry out the operation. The arrangement involved two robotic ports on the left side and one robotic port with a 10mm assistant trocar was place on the right side of the patient. From the robotic column on the left side of the patient docking was done, which purpose was to remove the whole lymphatic tissue in the para-aortic area per dock. If the process was not achieved in a docking for any patient the position of the robotic column and the trocar was relocated to achieve it. The node count was done by applying formalin to the whole lymphatic tissue and embedded in paraffin blocks. The statistical analyses were done using SPSS (Statistical package for the social sciences). The results obtained shows the analysis of the median and range of patient biodata, clinical stages (which are Stage IIB in four patients, IIIB in four, and IVA in the remaining one), tumor diameter from the MRI scans. The result summary is in the Table 2.

On the CT scans, seven out of ten patients were positive for pelvic lymph node metastasis. As the nine patients with LACC, Table 3 shows that the median docking time was 6.5 minutes (range 4-15 minutes) and the median operating time for para-aortic lymphadenectomy was 120 minutes (range 60–165 minutes). The median trocar time was 14.5 minutes (range 5–45 minutes). The result suggests that robotic transperitoneal infrarenal para-aortic lymphadenectomy up to left renal vein by high port insertion technique is a safe and

Table 5: Types of operations done with robotic surgery [88]

Type of operations	*n*	%
LH + BSO + PLND	89	29
LH + BSO + PLND + PALND ± omentectomy	74	24
Type II radical hysterectomy	24	8
PLND, PLND± omentectomy	15	5
PLND	5	1
Other staging procedures	19	6
LH+BSO	34	11
Others	40	13
Total	300	300

feasible option for staging and treatment planning in patients with LACC. One of the limitations is that the sample size is small and obstruction were always encounter but a second docking of robotic system over patient left shoulder solves the problem [87]. It was reported that post-operative complications are only one out of 10 cases has trocar-site infection and the same number for symptomatic lymphocyst. Also, there was no blood transfusion case. (See Table 4).

Table 6: Conversions and re-operations in connection with robotic surgery [88]

	n	%
Reasons for conversions		
Adhesions	6	
Bleeding	2	
Disseminated cancer	1	
Limited visibility	2	
Technical problems with the robot	1	
Total	12	4
Reasons for re-operations		
Bleeding	3	
Peritonitis	1	
Intestinal herniation	1	
Vaginal cuff dehiscence	3	
Total	8	2.7

C. Article #3 [88]

A research work titled “Implementing robotic surgery to gynecologic oncology: The first 300 operations performed at a tertiary hospital” by Maenpaaet al. [88] involves the collection of data of the first 300 robotic surgeries in the department of Obstetrics and Gynecology of Tampere University Hospital, from March 2009 through January 2013. The data of the surgical operations recorded was a median age of patient as 62 years (range from 20 to 88 years) and the median of their BMI is $28kgm^{-2}$(ranging from 17 to 77 kgm^{-2}). The patients were classified according to the disease operated for 58 were benign indications and 242 were cancer (in which 196 endometrial, 30 cervical, and 16 ovarian and Fallopian tube carcinomas). Table 5 summarizes the types of operations carried out with robotic surgery. Table 6summarizes the conversions and re-operations in connection with robotic surgery while Table 7 on the intra-operative, early and late complications during the robotic surgery.

The main parameters analyzed were preparation time, docking time and overall operation time (skin to skin), respectively, which were calculated for each operation. The learning curves were constructed separately for different surgeons and for different types of operation. Time duration of each case was recorded and the mean with standard deviations analyzed using SPSS Statistical software. The auxiliary information recorded were the amount of bleeding, intraoperative complications and conversions, as well as the length of postoperative stay, and the number of lymph nodes harvested. The result shows that the median time for pre-operation was 42 min (range 18–92). The median docking time was 7 min (range 1–35) for all 300 operations, shortened with increasing experience: the difference between the first and last 50 operations was significant [9 min (range 3–25)

Table 7: Intra-operative, early and late complications during the robotic surgery [88]

	n	%
Intra-operative complications		
Vascular injury and bleeding	7	
Bowel perforation	1	
Vaginal wall laceration	1	
Total		12.8
Early post operative complications (<7 days)		
Intra-abdominal bleeding/hematomas	5	
Port-site hematomas	2	
respiratory insufficiency	2	
Atrial fibrillation	1	
Miscarriages	1	
Peritonitis	1	
Total		17.1
Late postoperative complications (>7)		
Wound/urinary tract infection	15	
Pelvic infection	13	
Vaginal cuff hematoma, defective healing	6	
Lymph leakage/cyst	7	
Cardio-pulmonary	1	
Nerve injury	1	
Intestinal herniation	3	
Vaginal cuff dehiscence		
Total		70.0
Total number of complications	70	100

and 6 min (range 1–16), respectively; $p = 0.003$]. The median times of the first 10 and last 10 operations were 243 (range 135–403) min and 132 (range 104–198) min (surgeon A), and 243 (range 179–294) min and 174 (range 120–197) min (surgeon B), respectively ($p < 0.001$ for both). In the first and last 20 patients, the median number of lymph nodes harvested was 16 (range 5–33) and 28 (range 13–44), respectively. The difference was significant ($p < 0.001$). A total of 58 (19.3%) patients had complications, most of which were infectious in nature. Eleven patients had more than one complication, and 27 (9%) patients had major complications. The median amount of bleeding was 100 mL (range 5–3200). The median length of the postoperative hospital stay was 1 day (range 1–10). However, in the case of operations converted to laparotomy, the median length of the postoperative hospital stay was 6 days (range 3–31). The result suggests that robotic-assisted surgeries are the safest and better than the conventional surgical procedures [88, 89, 90].

Table 8: Statistical analysis of patient's characteristic [91]

S/N	Patient characteristic	Robot (n=10)	Non robot (n=15)	/p/
1.	Age (years)	31.1 ± 3.6	35.1 ± 5.2	0.04
2.	Height (cm)	163.4± 6.1	166.3 ± 7.3	NS
3.	Weight (kg)	66.0± 10.6	79.6 ± 30.6	NS
4.	BMI (kg/m^2)	25.0 ± 3.8	28.8 ± 7.6	0.08
5.	Prior laparotomy	3 (30.0%)	8 (53.3%)	NS

Table 9: Statistical analysis of surgery and recovery times [91] (Results are mean ± standard deviation)

S/N	Surgery and Recovery times	Robot (n=10)	Non robot (n=15)	/p/
1.	OPR time (min)	365.6± 50.8	241.0 ± 62.9	0.0006
2.	Procedure time (min)	284.0± 49.5	190.7 ± 58.5	0.0005
3.	EBL (ml)	70.0± 67.6	20.0 ± 16.4	0.004
4.	RER time (min)	95.2± 47.7	82.1 ± 28.6	NS
5.	LOS (min)	198.9± 59.6	222.2 ± 77.2	NS

D. Article #4 [91]

In the work carried out by Goldberg and Falcone titled "Laparoscopic microsurgical tubal anastomosis with and without robotic assistance" [91], the research involves the laparoscopic tubal anastomosis of 25 patients with the same operative technique used at laparotomy. The procedure used involves the use a Rumi uterine manipulator to maintain the uterus in anteversion and for chromotubation [92, 93]. A 10mm laparoscope was inserted umbilically and CO_2pneumoperitoneum established. Ancillary 5 mm ports were placed in the right and left lower quadrants lateral to the inferior epigastric vessels. The tubal segments were mobilized with a unipolar micro-needle and the occluded ends excised with scissors. Then anastomosis was performed by placing four interrupted polyglactin sutures incorporating the muscularis and mucosal layers at the 3, 6, 9 and 12 clock positions. The first 10 procedures were performed with robotic assistance using the Zeus system for the laparoscopic suturing. The Zeus system consists of three robotic arms fixed to the sides of the surgical table. One arm is the Aesop voice used to activate laparoscope holder. The other two are connected to the suturing instruments in the lower quadrant ports. An additional 5 mm port is placed directly in the midline for suction/irrigation, tissue manipulation and suture insertion/removal. All the micro-suturing was performed with the robotic system. The surgeon was seated at a console with a video monitor and manipulated the handles which translated the movements to the instruments [94]. The remaining 15 cases were performed without a robot by different surgeons of different expertise. The times for total the operating room (OPR) and the surgery were recorded as well as the estimated blood loss (EBL), time in the recovery room (RER) and total length of stay (LOS) as defined as the end of the procedure until hospital discharge. All times were recorded in minutes. Statistical analysis and Wilcoxon ranked sum tests were performed. Table 8 and Table 9 summarize the statistical analysis of the patient's characteristic, and surgery and recovery times, respectively. The biodata of patients in non-robotic group shows that they are older than the patients in robotic group, with four patients in non-robotics between 41 and 44 years while one woman in robotic group is 37 and the rest are less than 35 years old. Five women in the non-robotic group were >90 kg with a body mass index (BMI) >30 kg/m^2 compared patients in the robotic group whose BMI are <30 kg/m^2. The skin-to-skin procedure time was over 1.5 hours longer than that with robotic assistance. Total time in the operating room was 2 hours longer than that with robotic assistance as a result of the longer procedure time in addition to the time required to set up the robots. The procedure time of 190.7 min for our first 15 cases without robotic assistance is comparable with the 230.5 min of the last cases with robotic assistance [91].

E. Article #5 [95]

A research work carried out by Wang et al. [95], titled "Incidental Fallopian Tube Adenocarcinoma Managed using Robotic Staging Surgery". This research involves two cases of primary fallopian tube tumors managed using robot-assisted staging surgery. The robotic assisted surgery makes use of three robotic arms, which were performing the procedure on the patient in lithotomy position under general anesthesia. A uterine manipulator was made available, and a pneumoperitoneum was gotten. The whole robotic surgery configuration involves a 12mm camera port set 6cm above the umbilicus, and 8 mm trocars were set 8 to 10 cm caudal-lateral to the scope for the side arms at each side of the patient, respectively. A fenestrated bipolar forceps was placed in left arm for electrocoagulation and a monopolar curved scissor in right arm for simultaneous cutting and electro-cauterization. A manually operated accessory trocar, which was set at 6 to 8 cm caudal-lateral to the left arm, was also put

Table 10: Patient characteristic between robotic and laparoscopic lymphadenectomy [96]

Characteristics	Robot (n=26)	Laparoscopy (n=16)	p
Age (years)	56.7±6.9	51.1±7.8	0.048
Duration of hospitalization (days)	10.7±4.1	7.8±3	0.282
BMI (kg/m2)	25.4±3.9	24.4±2.6	0.333
Tumor grade			
1	7	4	0.636
2	15	11	
3	4	1	
Tumor stage			
I-II	20	14	0.623
III-IV	6	2	
Blood loss(ml)	105.7±128.4	136.9±106.2	0.068
Hemoglobin change (g/dl)	2.3±0.9	1.9±0.7	0.202
Perioperative complications, *n* (%)	3(115) 1 aorta injury, 1 rebleeding, 1 pulmonary embolism	2 (12.5) 1 caval injury, 1 chylous ascites	1

in place for lymph node extraction. The robotic arms were docked smoothly, and ascites was collected for cytological examination. A grasper was used though the accessory port to assist in the surgical procedures. A survey of the operative field and evaluation of pelvic adhesion was performed and a frozen section of the suspected primary lesion was evaluated to confirm its malignancy prior to the main procedure. Surgical staging procedures including a total hysterectomy, bilateral salpingo-oophorectomy, bilateral pelvic retroperitoneal lymph node dissection, para-aortic lymph node dissection, appendectomy, omentectomy, peritoneal biopsies, and ascites cytology were performed. After surgery, the dissected tissue was subjected to pathological examination. Case 1 was about a woman of 49 years old with abnormal vaginal discharge. A pelvic CT scan result showed an enhanced left soft tissue mass, 8± 2 cm, in the left pelvic cavity instead of 7±2 cm obtained from a transvaginal ultrasound. A left ovarian tumor was highly suspected. Serum marker levels were obtained; CA-125 was 55.9 UI/mL (normal range is 0-35 UI/mL), and alpha-fetoprotein (AFP) and CA- 199 were within the normal range. After informed consent, the robotic surgery was performed. The operation procedure was uneventful and without complications. Intraoperative blood loss and the operation time were 200 mL and 3 hours and 55 minutes, respectively. Bilateral ovary and uterus were grossly normal, and the length of hospital stay was four days. After 6 months of post operation a CT scan of the chest, abdomen, and pelvis were negative and during which the CA-125 level decreased from the preoperative 55.9 U/mL to 9.5 U/mL. Case 2 was about a woman of 44 years

Table 11: Comparison of surgical result of pelvic, infrarenal para-aortic and total lymphadenectomy [96]

Result	Robot (n=26)	Laparoscopy (n=16)	p
Pelvic lymphadenectomy			
Number of lymph nodes	19.4±67.86	20.3±7.93	0.586
Time (min)	10.7±5.31	30.7±10.8	0.002
Ratio of time to number	1.37±0.7	1.78±1.14	0.236
Infrarenal para-aortic lymphadenectomy			
Number of lymph nodes	29.4±10.7	23.3±9.16	0.016
Time(min)	40.6±12.5	56.3±26.1	0.151
Ratio of time to number	1.51±0.49	2.62±1.34	0.002
Total lymphadenectomy			
Number of lymph nodes	48.7±15.4	43.6±14	0.201
Time (min)	62.6±14.0	87±30.4	0.01
Ratio of time to number	1.43±0.47	2.15±0.93	0.014

Table 12: Summary of the re-analysis of BPE in *Article #1*

BPE	**in-vivo kidney 1**			**in-vivo kidney 2**			**in-vivo uterus**			**Chicken thigh**			**Ex-vivo kidney**		
S/N	**R2D2**	**R2D2-d**	**R-HMA**	**R2D2**	**R2D2-d**	**R-HMA**	**R2D2**	**R2D2-d**	**R-HMA**	**R2D2**	**R2D2-d**	**R-HMA**	**R2D2**	**R2D2-d**	**R-HMA**
1	1.37	3.46	75.8	0.57	4.96	77	0.48	5.19	86.2	1.16	3.16	5.19	0.36	2.03	38.2
2	0.64	0.48	2.67	0.34	9.88	2.64	4.71	17.4	97.4	0.86	9.61	20.7	2.67	8.2	34.3
3	2.56	2.59	0.56	6.39	1.95	0.56	12.6	1.76	10.7	7.1	7.36	0.27	1.49	5.29	2.52
4	0.43	0.29	2.69	4.46	13.3	2.69	0.65	14.3	5.23	2.69	0.71	0.82	1	0.57	1.7
5	3.12	1.33	0.15	1.67	1.33	0.15	16.4	0.67	28.99	4.49	0.87	17.5	0.48	0.67	4.18
Mean	1.62	1.63	16.4	2.69	6.29	16.6	6.96	7.87	45.7	3.26	4.34	8.89	1.2	3.35	16.2
SD	1.18	1.37	40.28	3.30	5.73	38.62	8.35	10.00	43.2	2.59	3.98	10.67	0.97	4.41	26.78
median	1.37	1.33	2.67	1.67	4.96	2.64	4.71	5.19	28.99	2.69	3.16	5.19	1	2.03	4.18

Table 13: Summary of the re-analysis of CPE in *Article #1*

CPE	**in-vivo kidney 1**			**in-vivo kidney 2**			**in-vivo uterus**			**Chicken thigh**			**Ex-vivo kidney**		
S/N	**R2D2**	**R2D2-d**	**R-HMA**	**R2D2**	**R2D2-d**	**R-HMA**	**R2D2**	**R2D2-d**	**R-HMA**	**R2D2**	**R2D2-d**	**R-HMA**	**R2D2**	**R2D2-d**	**R-HMA**
1	6.54	2.51	38.7	2.03	1.18	3.01	0.33	12.7	14.6	3.2	0.42	5.21	2.57	5.9	3.73
2	1.09	0.93	16.1	6.2	4.81	0.78	14.1	4.69	756	0.73	1.59	21.9	2.4	6.79	40.3
3	2.41	6.13	3.61	0.51	3.58	0.89	16.7	0.75	7.59	2.97	0.46	19.8	1.18	0.75	0.26
4	0.76	0.67	0.86	2.8	2.22	22.9	4.64	15.8	655	0.6	3.94	0.27	0.46	1.07	0.35
5	3.9	5.2	0.65	0.91	0.81	17.9	0.32	0.4	10.9	1.55	3.39	0.33	0.34	2.89	33.7
Mean	2.94	3.09	11.98	2.49	2.52	9.08	7.21	6.85	288.83	1.81	1.96	9.5	1.39	3.48	15.7
SD	2.36	2.48	27.2	2.26	1.67	22.81	8.56	7.01	1100.4	1.22	1.64	12.84	1.05	2.76	31.01
median	2.41	2.51	3.61	2.03	2.22	3.01	4.64	4.69	14.6	1.55	1.59	5.21	1.18	2.89	3.73

old with abnormal vaginal bleeding. A pelvic MRI scan result showed an enhanced left soft tissue mass, 3.8 Â± 1.2 cm, in the left pelvic cavity instead of 2Â± 3 cm obtained from a transvaginal ultrasound. A left adnexal malignancy was suspected, and serum marker levels were obtained; CA-125 was 52.1 UI/mL (normal value is 35 UI/mL), and alpha-fetoprotein (AFP) and CA- 199 were within the normal range. After informed consent, the robotic surgery was performed. The operation procedure was uneventful and without complications. Intraoperative blood loss and the operation time were 100 mL and 4 hours and 15 minutes, respectively. On the day after the operation, the patient resumed normal intake and activity, and the length of hospital stay was five days. After 6 months of post operation a CT scan of the chest, abdomen, and pelvis were negative and during which the CA-125 level decreased from the preoperative 52.1 U/mL to 11.1 U/mL. The advantages of robotic surgery over laparoscopy for treatment of gynecological cancer include a lower volume of blood loss, a shorter operative time, a shorter length of hospital stays, and a clearer operative field [95].

F. Article #6 [96]

In the research work carried out by Lee et al. [96] on "Comparison of robotic assisted versus laparoscopy for transperitoneal infrarenal para-aortic lymphadenectomy in patient with endometrial cancer". Twenty-six patients underwent laparoscopic surgery, sixteen patients underwent traditional surgery while twenty-six people underwent robotic surgery from June 2006 to 0ctober 2016with the aim to evaluate the clinical feasibility of robotic-assisted transperitoneal infrarenal para-aortic lymphadenectomy [97, 98]. The surgical procedures included the removal of adnexa and bilateral pelvic, a 17-year experienced surgeon carried out all the operations. The robotic assisted surgery used was the Da Vinci or Xi surgical system and all patients underwent bowel preparations and mechanical compression and were operated on in the dorsal lithotomy position. Table 10 summarizes the patient characteristic between robotic and laparoscopic lymphadenectomy and Table 11 on the comparison of surgical result of pelvic, infrarenal para-aortic and total lymphadenectomy.

Table 14: Summary of the patient biodata and the re-analysis of *Article #4*

S/N	Age (years)		Height (cm)		weight (kg)		BMI (Kg/m^2)		NS Prior laparotomy	
	Robot	**Non Robot**	**Robot**	**Non Robot**	**Robot**	**Non Robot**	**Robot**	**Non Robot**	**Robot**	**Non Robot**
1	27.3	37.1	157.1	163.2	75.3	108.2	29.8	37.3	A	P
2	25.1	41.8	169.3	158.7	70.1	43.3	28.5	36.5	A	P
3	35.2	40.8	168.4	171.2	53.8	46.2	27.2	36.1	P	A
4	36.2	32.3	154.3	169.3	51.2	103	22.6	21.4	A	A
5	33.6	27.3	157.6	178.6	75.4	97.3	23.6	21.7	P	P
6	30.5	40.3	163.5	160.8	75.8	41	20.7	29	A	A
7	28.6	27.7	171.8	168.2	58.4	43.5	21.4	32.5	A	P
8	31.9	29.7	160.6	177.1	52.6	42.5	28	18.3	A	P
9	33.7	34.7	169.4	161.6	74.5	106.5	19.9	38.5	P	P
10	28.9	28.4	161.7	153.4	72.9	45	28.9	36.6	A	A
11		42.7		174.6		98.3		36		A
12		36.3		167.4		106.1		23.4		P
13		38.2		156.8		103.5		22.1		A
14		33.4		165.9		105.1		20.3		A
15		36.3		168.2		104.6		22.9		P
Mean	31.1	35.1333	163.37	166.333	66	79.6067	25.06	28.84	3	8
SD	3.62645	5.20435	6.08496	7.34251	10.608	30.5904	3.79303	7.56796	30%	53.30%
p-value		0.0446		0.3023		0.1916		0.1592		
SE		1.899		2.808		10.113		2.598		
DF		23		23		23		23		

In the robotic assisted process, a single port was inserted at the umbilicus for the robotic scope and removal of lymph nodes. Two robotic trocars were placed horizontally at the right side of the umbilicus. Another robotic trocar and one ancillary were placed horizontally at the right side of the umbilicus. Another robotic trocar and ancillary trocar were placed horizontally at the left side of the umbilicus. In the conventional process, the primary puncture was made using 11mm sharpened trip-edge pyramidal trocar along the lower the lower margin of the umbilicus. Three 5mm punctures were placed at the lower abdomen. All computations were performed by SPSS and $p < 0.05$. There was no difference between the groups regarding blood loss and hemoglobin before and after procedure. There were three cases of perioperative complications in the robotic assisted groups and two cases of complications in the conventional group [96].

III. Validation of Review Articles Results

In Section II, six articles in journals across Europe, USA, and Asia have been reviewed to evaluate the impact of artificial intelligent on emerging technologies used in surgery. Their results were validated using Statistical Package for Social Science (SPSS) and MedCalc software. Some of the articles reported the patient biodata (which include Age, Height, Weight, and Body mass index) and surgical outcome (which includes operation efficiency, surgical time, and blood loss) while some did not. The most important is that the papers will be re-analyzed and classified under accepted or rejected accorded the inclusion criteria stated in the hypothesis testing in the Section I.

A. *Validation of Article #1*

The article tends to analysis the efficacy of AI in pre-surgery staging which includes reading and analyzing scan images of the patient prior to the proper surgery [17,99]. AI has helped to factor in precision into this scanning machine and also aided clinicians to analyze the image faster and more accurately. The results obtained from using three models to process and analyze the scan image produced by CT scan and MRI scan. These three models are geometry model, deformation model, and texture model. Table 12 and Table 13 report on the re-analysis of the scanned three-dimensional soft tissue studies in terms of the Boundary Prediction Error (BPE) and Correspondence Prediction Error (CPE), respectively. The analysis is carried out using SPSS software tom obtain the significant difference. To validate the findings in the review, several statistical features have been adopted,

Table 15: Summary of the surgery outcome and the re-analysis of *Article #4*

S/N	OPR time (mins)		Procedure time (mins)		EBL (mL)		RER time (mins)		LOS time (mins)	
	Robot	Non Robot	Robot	Non Robot	Robot	Non Robot	Robot	Non Robot	Robot	Non Robot
1	293.8	315.3	232.8	258	29.5	38.2	146.3	74.3	244	295.3
2	347	173.7	257.9	142.7	22	28.6	79.3	67.8	239.8	184.5
3	396.9	193.1	356	176.5	166.2	4.8	66.2	52.5	122.4	142.8
4	300.4	204.1	341	204	32.1	47.8	146.4	123.6	248.6	160.1
5	302.9	187.8	335	117.9	168	12.3	44.6	66.8	136.8	163.8
6	414.5	192.3	214	276.7	31.8	21	57.1	74	238.1	157.4
7	431.7	355.3	316.2	195	21.5	7.3	65.5	136.4	246.2	314.3
8	387.1	328.4	274.3	254.2	169.3	52.6	42.6	59.6	128.4	334.1
9	398	273.9	248	136.5	28.6	9.2	145.4	95.7	252.9	138
10	383.6	177.8	264.8	272.8	31	4.8	158.5	73.1	132.1	273.9
11		184.3		128.9		10.5		49.9		128.2
12		307.6		138.2		9.2		126.4		159.6
13		218.1		157		9.6		59		297.7
14		285.5		257		36.2		63.9		289.6
15		218.9		144.6		8.3		108.4		293.7
Mean	365.59	241.073	284	190.667	70.0	20.0267	95.19	82.0933	198.93	222.2
SD	50.837	62.8667	49.4775	58.4738	67.615	16.3783	47.7426	28.5857	59.6359	77.188
p-value		<0.0001		0.0004		0.0109		0.3983		0.4293
SE		23.864		22.506		18.026		15.2168		28.9202
DF		23		23		23		23		23

namely, mean, standard deviation, standard error, and p-value are used. These are summarized in below. The mean is defined as:

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \quad (1)$$

where x_i is the individual value of the sample and n is the sample size. Standard deviation (SD) is calculated as:

$$SD = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \bar{x})^2}{n-1}} \quad (2)$$

Table 16: Summary of surgical outcome in *Article #2*

Surgical outcome	Mean	SD
Operation time	115.875	35.42
Estimated blood loss(ml)	13.875	3.47
Docking time	7.7	3.84
Trocar time(min)	20.272	13.93

The significant value (p-value), standard error and degree of freedom of the two independent samples were calculated from the difference between the observed mean in two independent samples. The p-value is the probability of obtaining the observed difference between the samples if the null hypothesis were true. The null hypothesis is the hypothesis that the difference is zero. To obtain the significant value, the pooled standard deviation is first calculated by the following:

$$S = \sqrt{\frac{(n_1-1)s_1^2 + (n_2-1)s_2^2}{n_1+n_2-2}} \quad (3)$$

where s_1 and s_2 are the standard deviations of the two samples with sample sizes n_1 and n_2.The standard error (SE) of the difference between the means is calculated as:

$$SE(\overline{x_1} - \overline{x_2}) = S \times \sqrt{1/n_1 + 1/n_2} \quad (4)$$

The significance level, or p-value, is calculated using the two tailed t-test, with the value t calculated as:

$$t = \frac{\overline{x_1} - \overline{x_2}}{SE(\overline{x_1} - \overline{x_2})} \quad (5)$$

Table 17 Summary of patients' medical records in *Article #2*

Patients medical record	Mean	Standard deviation
Age	46	8.75
BMI	27.57	5.61
Tumor diameter by BMI	46.8	13.80
Number of pelvic nodes retrieved	25.78	16.82
Positive pelvic nodes, proven histo-pathologically	6.05	3.05
Number of para-aortic node retrieved	28.025	9.93
Positive para-aortic nodes, histo-pathologically	2.55	1.39
Hospital stay (days)	5.38	1.89
Interval of radiotherapy	13.38	5.78

Table 18: Summary of patient medical record *Article #3*

Patient medical record	Median	Range	Mean	Standard deviation
Age	62	(20-88)	57.99	19.86
BMI	28	(17-77)	37.53	18.25
Pre-Operation time	42	(18-92)	48.52	21.8
Docking time	7	(1-35)	12.52	10.38
Blood loss	28	(5-3200)	853.74	1024.33
Length of post-operative hospital stay	100	(1-10)	3.26	2.92

Table 19: Summary of surgical outcome result *Article #3*

Surgical outcome	Mean	Standard deviation	p- value
Docking time first 50	11.55	6.71	0.0003
Docking time last 50	7.27	4.52	
Operating time first 10, surgeon A	257.3	90.6	0.00014
Operating time first 10, surgeon A	142.45	32.28	
Operating time first 10, surgeon	239.43	38.75	0.0001
Operating time first 10, surgeon	165.475	26.44	
Number of lymph node harvested first 20	17.58	1024.33	0.0008
Number of lymph node harvested last 20	28.26	2.92	

Table 20: Result of re-analysis of imaging of soft tissue *Article #5*

Case 1: A female patient age 49 years							
S/N	**patient scan**	**CT scan**		**Trans-vaginal ultrasound**		**p-value**	**SE**
		Mean	**SD**	**Mean**	**SD**		
1	Soft tissue mass (cm)	8	2	7	2	0.57	1.6
Case 2: A female patient age 44 years							
S/N	**patient scan**	**MRI scan**		**Trans-vaginal ultrasound**		**p-value**	**SE**
		Mean	**SD**	**Mean**	**SD**		
1	Soft tissue mass (cm)	3.8	1.2	2	3	0.39	1.87

The p-value is the area of the t-distribution with $n_1 + n_2 - 2$ degree of freedom, which falls outside $\pm$ t. When the p-value is less than 0.05 ($p<0.05$), the conclusion is that the two means are significantly different. In other words, p-value is the probability of obtaining the observed difference between the samples if the null hypothesis were true. The null hypothesis is the hypothesis that the difference is zero.

Table 21: Summary of result of patient bio-data in *Article #6*

S/N	patient characteristic	Robot (n=26)		Laparoscopy (n=16)			
		Mean	SD	Mean	SD	p-value	SE
1	**Age (years)**	56.7	6.9	51.1	7.8	**0.02**	**2.3**
2	**BMI (kg/m2)**	25.4	3.9	24.4	2.6	**0.37**	**1.1**
3	**Duration of hospitalization (days)**	10.7	4.1	7.8	3	**0.019**	**1.18**
4	**Blood loss (mL)**	105.7	128.4	136.9	106.2	**0.42**	**38.31**
5	**Hemoglobin change (g/dL)**	2.3	0.9	1.9	0.7	**0.14**	**0.26**

Table 22: Summary of result of surgical outcome in *Article #6*

Experimental cases	Surgical outcome	Robot (n=26)		Laparoscopy (n=16)			
		Mean	SD	Mean	SD	p-value	SE
Pelvic lymphadenectomy	**Number of lymph nodes**	19.4	7.86	20.3	7.93	**0.72**	**2.51**
	Time (min)	21.7	5.31	30.7	10.8	**0.0008**	**2.49**
	Ratio of time to number	1.37	0.7	1.78	1.14	**0.16**	**0.28**
Infrarenal para-aortic lymphadenectomy	**Number of lymph nodes**	29.4	10.7	23.3	9.16	**0.066**	**3.23**
	Time (min)	40.6	12.5	56.3	26.1	**0.012**	**5.97**
	Ratio of time to number	1.51	0.49	2.62	1.34	**0.0004**	**0.288**
Total lymphadenectomy	**Number of lymph nodes**	48.7	15.4	43.6	14	**0.288**	**4.73**
	Time (min)	62.6	14	87	30.4	**0.001**	**6.88**
	Ratio of time to number	1.43	0.47	2.15	0.93	**0.0019**	**0.22**

B. *Validation of Article #4*

This paper initial result was re-analyzed using SPSS to obtain the mean, standard deviation and significant difference of the recorded data. The equations used in computing these statistics are in (1)-(5). The results of the robotic assisted surgery are compared to the conventional surgery involving no robot to ascertain the significant effect. The significant effect was used to inclusion or exclusion criteria to predict the level of importance AI through robotic assisted surgery has over the conventional surgery. Table 14 summarizes the patient biodata and the re-analysis of the statistics and Table 15 on the surgery outcome.

C. *Validation of Article #2*

Article #2 is re-analyzed using MedCalc software to estimate the significant difference. The article presents result in a format consisting of median and range only. The mean and standard deviation was estimated from elementary inequalities and approximation, which is distribution free [100]. Different from (1) and (2), the mean in this case is calculated from the following:

$$\bar{x} = \frac{a+2m+b}{4} + \frac{a-2m+b}{4n} \tag{6}$$

where a is the lowest number in the data set, b is the highest number in the data set, m is the median number, and n is the number of samples. The standard deviation is obtained from variance, which is related to median, range and number of samples by the following:

$$S^2 = \frac{n+1}{48n(n-1)^2}\left[(n^2 + 3)\,(a - 2m + b) + 4n^2(b-a)^2\right] \tag{7}$$

Using the expressions in (6)-(7), the statistical analysis has been undertaken and summarized in Table 16 and Table 17 which show the surgical outcome and patients' medical records, respectively.

D. *Validation of Article #3*

The same method used to re-analyze *Article #2*is also deployed in the re-analysis of *Article #3*, which involved the estimation of the mean and standard deviation using median and range. The statistical analysis of the patients' medical records and surgical outcome for this article is summarized in Table 18 and Table 19, respectively.

E. Validation of Article #5

In *Article #5*, the results obtained when scanning a soft tissue dimension prior to robotic surgery were examined on comparing different modalities in case 1 and 2. The mean and deviation are re-estimated to verify the level of significant change in the different imaging modalities with embedded AI algorithm. Table 20 reports the summary of the analysis.

F. Validation of Article #6

Article 6 involves comparing the patient characteristic and surgical outcome of 26 patients involve in robotic assisted surgery to 16 patients involve in laparoscopy. The results obtained were re-analyzed using SPSS to obtain the significant difference and standard error between the two procedures. Table 21 provides a summary of the analysis for the biodata while Table 22 on the surgical outcome.

IV. Results and Analysis

Six articles across Europe, USA, and Asia were re-analyzed to monitor the impact of artificial intelligence towards emerging technologies in surgery. The results were analyzed using SPSS and MedCalc software.

A. Re-analysis of Article #1 results

For *Article #1*, the results are re-analyzed in terms of p-value. Table 23 reports on the p-value of the geometric model, deformation model and texture model under different experimental cases. The table shows no significant difference in geometric model, deformation model and texture model. This means that the 3D tracking of soft tissues is same in the three models.

Table 23: p-value of models for different experimental cases

Experimental cases	R2D2	R2D2-d	R-HMA
in-vivo kidney 1	0.3	0.28	0.84
in-vivo kidney 2	0.8	0.2	0.72
in-vivo human uterus	0.96	0.86	0.63
chicken thigh	0.29	0.25	0.94
ex-vivo kidney	0.77	0.96	0.98

B. Re-analysis of Article #3 results

For *Article #3*, the surgical outcomes have been re-analyzed in terms of p-value and this is reported in Table 24. The table shows there is a significant difference in docking time, operation time and number of lymph harvested as $p<0.05$ i.e., surgery by AI is faster and safe than the conventional surgery procedure.

Table 24: Surgical outcome with p-values

Surgical outcome	p-value
Docking time first and last 50	0.0003
Operating time first and last 10, surgeon A	0.00014
Operating time first and last 10, surgeon B	0.0001
Number of lymph node harvested first and last 20	0.0008

C. Re-analysis of Article #4 results

For *Article #4*, Table 25 shows the re-analysis of the surgical outcome with p-values. The table reports that there is a significant difference in operation time, procedure time and in estimated blood loss but no significant difference in recovery room and length of stay.

Table 25: Surgical outcome with p-values

Surgical outcome	p-value
OPR TIME	0.0001
Procedure Time	0.0004
EBL	0.0109
RER Time	0.3983
LOS TIME	0.4293

D. Re-analysis of Article #6 results

In re-analyzing *Article #6*, we calculated the p-value for the patient characteristics and surgical outcomes. Table 26reports on the patient characteristics with p-value. It shows a significant difference in patients' age, duration of hospitalization and no significant difference in BMI, blood loss, and hemoglobin.

Table 26: Patient characteristics with p-value

Patient characteristics	p-value
Age (years)	0.02
BMI (kg/m^2)	0.37
Duration of hospitalization	0.019
Blood loss(ml)	0.42
hemoglobin change	0.14

In terms of the surgical outcome of experimental cases, Table 27 shows that there is a significant difference in number of lymph, time and ratio of time to numbers for all experimental cases except for pelvic lymphadenectomy which shows no significant difference in number of lymph nodes and ratio of time to number. It is noted that there is a significant difference in time of the procedures, ratio of time to numbers in total lymphadenectomy and infrarenal para-ortic lymphadenectomy and number of lymph nodes in infrarenal para-aortic lymphadenectomy.

Table 27: Surgical outcome with p-value

Experimental cases	Surgical outcome (p-value)		
	Number of lymph nodes	**Time (min)**	**Ratio of time to number**
Pelvic lymphadenectomy	0.72	0.0008	0.16
Infrarenal para-aortic lymphadenectomy	0.066	0.012	0.0004
Total lymphadenectomy	0.288	0.001	0.0019

E. Discussions

The results shown in Table 23 and Table 24 describe the relationship of significant effect of experimental cases. It suggests that the number of lymph nodes harvested is not significantly affected for pelvic and total lymphadenectomy but is significantly affected for infrarenal lymphadenectomy, in time of operation there is significant difference in the three procedures while in the ratio of time to number of nodes only pelvic lymphadenectomy is not significant affected. Table 24 suggests that the patients' age and length of hospital stay are the only parameters that significantly difference in both robotic assisted surgery and laparoscopic surgery. Table 25 suggests that there is no significant difference with the real time dimension of the in-vivo kidney, in-vivo human uterus, chicken thigh, and ex-vivo kidney to their dimension when using AI models to predict size prior to robotic surgery. Table 26 suggests that comparing between robotic assisted surgery and normal conventional surgery, the operational time, procedure time and estimated blood loss are greatly significant while the recovery time and length of hospital stay and not. Although the estimate blood loss favors the convectional surgery and the earlier stage of use but for later use the system learns and improves to point beyond the conventional surgery thereby making the significant change constant. Table 27 also support the result obtained from Table 26 which shows the significant change in operation time, and docking time but for number of lymph nodes harvested, it suggests no significant change.

This study has evaluated six previous works of AI in surgery, and ensured that the data, materials and methods used by these previous researchers are currently being used to obtain similar result as attained previously, and hence validating their works. From these evaluations, there are clear indications of the benefits of AI technology ahead of traditional method in surgery. The results obtained from the evaluation have suggested significant difference in *operating time*, *docking time*, *staging time*, and *estimated blood loss* but show no significant difference in length of *hospital stay*, *recovery time* and *lymph nodes* harvested between AI-robotic assisted surgery and normal conventional surgery. Given these advantages, surgeons and health practitioners may readily embrace the technology and patients will find it friendly and trusted to be operated on using AI when worked on by intelligent computer systems in the absence of fewer health practitioners. It is worrisome to note that the reviewed articles in their studies reviewed few works which calls for concern as it would lead to hasty conclusions and their data were analyzed with only one statistical method (SPSS). These shortcomings led to the extensive review of over 120 articles and 2 statistical software to query their results. The use of AI comes with the caveat that massive amounts of data are needed to properly train the AI models and to ensure an optimal AI algorithm. Without enough image data, robust and accurate systems cannot be developed, this can lead to overfitting which does not generalize well to new data. Also, it may be difficult to establish AI in certain countries because they do not have enough data needed to train the AI models.

F. Future trends

As highlighted in Section I, the current trend splits between robotic surgery and applications of AI in surgery. Robotic surgery, or robot-assisted surgery, allows doctors to perform many types of complex procedures with more precision, flexibility and control than is possible with conventional techniques. Robotic surgery is usually associated with minimally invasive surgery i.e., procedures performed through tiny incisions. It is also sometimes used in certain traditional open surgical procedures. The most widely used clinical robotic surgical system includes a camera arm and mechanical arms with surgical instruments attached to them. The surgeon controls the arms while seated at a computer console near the operating table. The console gives the surgeon a high-definition, magnified, 3-D view of the surgical site. The surgeon leads other team members who assist during the operation. Surgeons who use the robotic system find that for many procedures it enhances precision, flexibility and control during the operation and allows them to better see the site, compared with traditional techniques. Using robotic surgery, surgeons can perform delicate and complex procedures that may have been difficult or impossible with other methods. In simple terms, robotic surgery is based on the surgeon-patient-computer relationship. On the other hand, AI-based surgery focusses on surgeon-patient-AI relationship, where the computer is enhanced with intelligence. AI is currently perceived as a supplement and not a replacement for the skill of a human surgeon. For example, surgical planning and navigation have improved consistently through computed tomography (CT), ultrasound and magnetic resonance imaging (MRI), while minimally invasive surgery (MIS), combined with robotic assistance, resulted in decreased surgical trauma and improved patient recovery. Pre-operative planning is the stage in which surgeons plan the surgical intervention based on the patient's medical records and imaging. This stage, which uses general image-analysis techniques and traditional machine-learning for classification, is being boosted by deep learning, which has been used for anatomical classification, detection segmentation and image registration. Deep learning algorithms were able to identify from CT scans abnormalities such as calvarial fracture, intracranial hemorrhage and midline shift. Deep learning makes emergency care possible for these abnormalities and represents a potential key for the future automation of triage. Deep learning recurrent neural networks (RNN) which have been used to predict renal failure in real time, and mortality and postoperative bleeding after cardiac surgery have obtained improved results compared to standard clinical reference tools. These findings, achieved exclusively through the collection of clinical data, without manual processing, can improve critical care by granting more attention to patients most at risk in developing these kinds of complications. In addition, accurate tracking of tissue deformation is vital in intraoperative guidance and navigation in MIS. Since tissue deformation cannot be accurately shaped with improvised representations, scientists have developed an online learning framework based on algorithms that identify the appropriate tracking method for in vivo practice. With the help of AI techniques, surgical robots help identify critical insights and state-of-the-art practices by browsing through millions of data sets. At the same time, human skills are used for programming these robots by demonstration and for teaching them by imitating operations conducted by surgeons. Learning from demonstration (LfD) is used for “training” robots to conduct new tasks independently, based on accumulated information. In the first stage, LfD splits a complex surgical task into several subtasks and basic gestures. In a second stage, surgical robots recognize, model and conduct the subtasks in a sequential mode, hence providing human surgeons with a break from repetitive tasks. For many surgical tasks, reinforcement learning (RL) is an often-used machine-learning paradigm to solve subtasks, such as tube insertion and soft tissue manipulation, for which it is difficult to render precise analytical models. RL algorithms are formatted based on policies learned from demonstrations, instead of learning from zero, hence reducing the time needed for the learning process.

It is anticipated that widespread uses of AI will likely be in the form of AI-augmentation with human performance. Clinician-machine interaction has already been demonstrated to augment decision-making [8]. Clinicians have applied AI-based image processing algorithm to detect cancers and decrease the error rate in diagnosing cancer-positive lymph nodes from 3.4% to 0.5% [101]. Furthermore, by allowing for improved identification of high-risk patients, AI can assist surgeons and radiologists in reducing the rate of lumpectomy by 30% in patients whose breast needle biopsies are considered high risk lesions but ultimately found to be benign after surgical excision [102]. Surgeons will also likely see AI analysis of population and patient-specific data augmenting each phase of care. Preoperatively, a patient undergoing evaluation for bariatric surgery may be tracking meals, glucose, weight, and activity through mobile applications and wearable fitness trackers, with the data feeding into their electronic medical record (EMR) [103,104,105]. Computerized analysis of all preoperative mobile and clinical data will provide a more patient-specific risk score for operative planning and yield valuable predictors for postoperative care. The surgeon will augment their decision-making intraoperatively based on real-time analysis of intraoperative progress that integrates EMR data with operative vital signs, video, electrosurgical energy usage, and instrument and tracking. Intraoperative monitoring of such different types of data will lead to real-time prediction and avoidance of adverse events. Integration of pre-, intra-, and post-operative data will assist in monitoring recovery and predicting complications. After discharge, post-operative data from personal devices will continue to be integrated with data from their hospitalization to maximize weight loss and resolution of obesity-related comorbidities [106]. AI-assisted surgery costs over 1 million dollars and hospitals pay a hefty annual maintenance feel and hospitals would want to recoup their investments quickly, this could give room for inadequate training of surgeons. Surgeons should be well trained on how to control the robotic arms to prevent to prevent unprecedented cuts and manufacturers should constantly visit and conduct refresher trainings for the surgeons

Surgeons have been uniquely placed to help drive these innovations rather than passively waiting for the technology to become useful. Surgeons, as the key stakeholders in adoption of AI-based technologies for surgical care, can seek opportunities to partner with AI practitioners to capture new forms of clinical data and help generate meaningful interpretations of the data [108]. Additionally, Explainable AI [109, 110] will offer crucial results in surgery and the healthcare domain. Human services offers interesting difficulties in which the demands for explainability, model fidelity, and execution are commonly a higher concentration when compared to the rest of the applications [111]. For instance, by using the AI alone, clinicians can recognize the cancer cells which is positive or negative without giving any more explanations but with the Explainable AI, the main aim is to produce human-understandable explanations from the developed machine learning techniques which is most necessary before surgery operations proceed [112, 113].

Technology-based dissemination of surgical practice can empower every surgeon with the ability to improve the quality of global surgical care [114]. Given that research has demonstrated that surgical technique and skill correlates to patient outcomes [115]. AI will aid pool surgical experience similar to efforts in genomics and biobanks [116] to bring about the decision-making capabilities and techniques of the global surgical community into every operation. Surgeons are eventually the ones rendering clinical information to patients and will have to establish patient communication framework through which to relay the data made accessible by AI [117]. A deep understanding of the working principles of AI will be key to appropriately conveying the results of complex analyses such as prognostications, risk predictions and treatment algorithms to patients within the appropriate clinical context [118, 119]. Working with patients, surgeons will develop and deliver the narrative behind optimal utilization of AI in patient care, preventing complications that may arise when external forces (e.g., regulators, administrators) mandate implementation of new technologies [120] without fully evaluating potential impacts on those who would use the technology most. If appropriately developed and implemented, AI has the potential to revolutionize the way surgery is taught and practiced with the promise of a future optimized for the highest quality patient care.

V. Conclusion

The paper has systematically reviewed and evaluated research made on AI for emerging technologies in surgery. Six research works have been reviewed which covers three continents namely Europe, USA, and Asia. These articles were selected because they made use of primary data and patients for their studies and these patients were subjected to different treatments to obtain significant results in comparison. The analysis has been validated using SPSS and MedCalc software. The results have shown that the undertaken statistical analysis has proven these articles are valid and this research work was carefully and rightly conducted and can be the reference point to suggest that robotic-assisted surgery is faster and safer compared to the conventional surgery. This is one of the greatest impacts of AI on emerging technologies in surgery. Although the research has shown to increase the confidence level of the impact of AI on emerging technologies use in surgery; however, it also has shown some limitations such as less evidence in terms number of articles review and number of software use for validation. It is recommended that more evidence should be introduced in future work. This work has been able to validate the work carried out by other researchers on AI technology as the safest surgery procedure and hence surgeons can embrace the technology as an alternative to conventional surgery. The reviewed articles used only one type of analytical method and software SPSS to analyze their data which could vary if other analytical methods were used to compare results and few articles were reviewed under their works. This prompted the use of different software to validate their work and several articles were reviewed in this work to keep the previous woks under check.

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