

Review

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Training in robotic pancreatic surgery

Sam Body¹, Michal Kawka², Tamara M.H. Gall^{3,4} 

¹Royal Bournemouth Hospital, Bournemouth BH7 7DW, UK.

²Imperial College school of medicine, South Kensington, London W12 0HS, UK.

³Department of Surgery, Royal North Shore Hospital, Sydney NSW 2065, Australia.

⁴Department of Surgery and Cancer, Imperial College, London W12 0HS, UK.

Correspondence to: Tamara M.H. Gall, Department of Surgery, Royal North Shore Hospital, Reserve Road, Sydney NSW 2065, Australia. E-mail: tamara.gall1@nhs.net.

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Abstract

The aim of this narrative review is to discuss current training for the robotic approach to pancreatic surgery and the potential use of machine learning to progress robotic surgical training. A literature search using PubMed and MEDLINE was conducted to investigate training programmes in robotic pancreatic surgery and advances in the use of artificial intelligence for training. The use of virtual reality can assist novice robotic surgeons in learning basic surgical skills. The use of automated video analytics can also improve surgical education to enable self-directed learning both within and outside the operating room. The emerging role and novel applications of machine learning in robotic surgery could shape future training by aiding the autonomous recognition of anatomical structures in the surgical field, instrument tracking and providing feedback on surgical competence. Training should be standardised to ensure the attainment of assessment benchmarks and include virtual simulation basic training in addition to procedural-specific training. Standardised procedural techniques should be used to improve patient safety, theatre efficiency and the continuation of robotic practice.

Keywords: Pancreatic, surgery, robotics, machine learning

INTRODUCTION

Why develop robotic training?

Minimally invasive surgery (MIS) has consistently demonstrated a number of advantages over open



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surgery^[1] and the benefit of smaller incisions has resulted in MIS becoming the standard approach for many operations^[2,3]. In several surgical specialities, such as colorectal and bariatrics, most procedures are performed using an MIS technique. MIS has not yet been widely embraced in hepato-pancreato-biliary (HPB) surgery, specifically pancreatic surgery. This is largely because of the nature of complex resections, proximity to major vessels requiring precise tissue dissection and small calibre lumen anastomoses that make a laparoscopic approach technically difficult^[4-6]. There is a considerable learning curve for laparoscopic pancreaticoduodenectomy (LPD); in a study, researchers reported that 104 procedures are required before proficiency is achieved^[7].

The delay in the uptake of pancreatic MIS is also partly because of perceived poor outcomes. In several studies, researchers have shown an increase in 30-day mortality with LPD^[8-10], which is thought to be because of low-volume complex procedures and the absence of an adequate surgical training programme^[8-11].

Robotic surgery, the next generation of MIS, has overcome many of the technical limitations of laparoscopy^[12-16]. The advances include a high-resolution three-dimensional (3D) camera and articulated instruments that have seven degrees of motion and eliminate physiological tremors. The resulting increased dexterity and improvement in hand-eye coordination enhance surgical precision. This has led surgeons to perform operations that were traditionally not amenable to, or difficult to perform with, minimal access techniques^[17,18]. The first robotic pancreaticoduodenectomy (RPD) was performed by Giulianotti in 2003^[19] and there are now several studies in which researchers have reported robotic surgery to be beneficial for technically complex procedures^[12-16]. Furthermore, there is increasing evidence that robotic pancreatic resections, in trained and experienced hands, are feasible and safe, with morbidity, mortality and oncological outcomes comparable to other surgical techniques^[14,20,21].

As robotic surgery is gaining momentum in other surgical specialities, an increasing number of hospitals now have access to robotic theatres^[22]. From 2010 to 2017, there was an increase of 2360% in the number of general surgical robotic operations in the US^[23]. In a recent study on trends in minimally invasive pancreaticoduodenectomy in the US, researchers showed that there was an overall decrease in the use of conventional laparoscopy and an increase in the use of robotics over the last few years^[24]. In England, there was a 410% increase in robotic surgery between 2013 and 2019^[25]. Thus, the continued evolution of robotic surgery is considered to be inevitable and there is now a strong drive for robotic pancreatic surgery to expand.

Robotic surgery requires different technical skills from both open and laparoscopic surgery. New operative conditions that need to be managed include the separation of the console surgeon from the operative field, absence of direct perception of the position of surgical instruments outside the visual field and absence of haptic feedback^[26,27]. During early experiences with robotic pancreatic surgery, the loss of haptic feedback was thought to potentially increase blood loss. However, it has since been shown that improved visual feedback by magnified 3D vision offers greater visualisation and control of splenic vessels, which leads to improved outcomes and a higher splenic preservation rate in robotic pancreatic surgery compared with laparoscopic distal pancreatectomy [106/198 (53.6%) and 76/281 (27.0%), respectively; $P < 0.0001$]^[26].

A significant drawback of robotic surgery has been the high cost, particularly associated with increased perioperative costs, which are likely to deter centres in low-income countries. However, many centres have shown reduced post-operative costs because of a shorter length of stay and improved post-operative outcomes^[28-30]. With the increasing use of robotic surgery, subsequent competition between robotic

platforms and future technological innovation, a reduction in cost is hopeful and would enable further implementation and access to minimal access surgery^[29].

In the majority of centres worldwide, robotic pancreatic operations are usually low-volume procedures. Therefore, without deliberate training outside the operating room, it is challenging to develop adequate robotic skills to become familiar with complex resections and this will limit the growth in robotic pancreatic resections. Researchers have shown that a comprehensive procedure-specific robotic training protocol for pancreatic surgery can improve the initial learning curve from training and simulation to the live operating phase^[31]. Note that, inevitably, the learning curve also depends on a surgeon's experience with open and laparoscopic surgery^[32]. Robotic training should enhance the acquisition of these robotic technical skills, potentially shortening the learning curve. Training programmes should aim for the participant to develop mastery of the procedure within a standardised environment, which must be introduced to ensure the safe introduction and expansion of this technology.

METHODS

A non-systematic search of the MEDLINE and Embase databases was performed on 5 July 2022 to identify relevant studies in which current training pathways in HPB robotic surgery were assessed. Search terms included the following, individually or in combination: “*hepatobiliary*”, “*pancreas*”, “*robotic*” or “*minimally invasive*” and “*training*”; in addition to “*machine learning*”, “*video analysis*”, “*computer vision*”, “*neural networks*” and “*surgery*”. Articles were included if they were in English or translated into English and included robotic pancreatic training. After titles and abstracts were screened, full-text articles and references were reviewed. Conference abstracts were excluded.

DISCUSSION

How should surgeons train?

The Miami Consensus guidelines on minimally invasive pancreas resections strongly recommend that all surgeons interested in performing MIS HPB procedures participate in a structured training programme^[33]. This is supported by the Society of American Gastrointestinal and Endoscopic Surgeons^[34]. A training programme should include virtual reality simulation, inanimate bio-tissue model work to practice dissection and anastomotic techniques, surgical video review, on-site proctoring and remote tele-mentorship. Following formal training programmes, a steep increase in the use of MIS has been seen, with reduced blood loss and conversion rates^[35].

Specific to RPD, a five-step proficiency-based robotic curriculum has been described by the University of Pittsburgh Medical Center^[36,37]. The five steps are (1) a proficiency-based virtual reality simulation curriculum; (2) an inanimate bio-tissue curriculum; (3) video library training; (4) an intra-operative evaluation; and (5) skill maintenance with ongoing assessment. The European-African HPB Association (E-AHPBA) has now also developed a European training programme for RPD based on the Pittsburgh technique.

The simulation curriculum is delivered using the inbuilt Da Vinci robotic system (Intuitive Surgical Inc. Mountain View, CA) simulation exercises. Simulation should be the first stage of console training for all robotic procedures. An understanding of the system, instrument manipulation and fourth arm integration, camera skills, energy device and needle control needs to be established. After each module, an automated score is calculated from performance metrics, including time to completion, the economy of motion, instrument collisions, instrument force, instruments out of view and master workspace range. Progression through the curriculum is based on the achievement of target scores for individual tasks. The median time

to complete “mastery” level is 4.5 to 7 h^[36]. This basic robotic simulation programme can be effectively introduced at an early postgraduate stage of training^[38].

During the second stage of the programme, participants use box trainers to perform a pancreaticojejunostomy, hepato-jejunostomy and gastro-jejunostomy using bio-tissue created to mimic the respective organs. This allows the development of a standardised technique to improve efficiency in the operating room, and enables adjustment to the loss of haptic feedback and recognition of the level of finger pressure required to exert the intended instrument force. Each practice anastomosis is recorded and later video scored by trained experts. Specific scores are required before progression to the next step.

All candidates later watch live cases in addition to several recordings of procedures, divided into distinct operative phases. The curriculum participants then progress to intra-operative performance under the guidance of a trained mentor with a step-wise progression of the number of operative phases performed. An evaluation of the RPD training programme showed that fellows increasingly perform the complete procedure and outcomes improve after they complete all curricula steps^[39].

To ensure that robotic surgery is performed safely in an experienced setting, pancreatic robotic training should be recommended to surgeons with specific characteristics that work in centres with defined surgical volumes. The E-AHPBA course requires that at least 50 PD per year are performed at the applicant’s centre, robot time is secured in the theatre and at least two surgeons are trained^[40]. Morbidity and mortality in MIS pancreatic resections is higher in low-volume centres^[41,42]; thus, the Miami guidelines recommend that centres participating in MIS should perform more than 20 MIS pancreas resections per year^[33]. This leads to the questions of where future training will take place, and if an organised link between low- and high-volume centres is required^[43].

Does HPB robotic training work?

There is a shorter learning curve for robotic surgery compared with laparoscopic surgery, with novices able to achieve basic surgical skills, including suturing and knot tying, more quickly^[44]. Furthermore, significant improvements in outcomes after pancreaticoduodenectomy have been shown in robotic surgery after 40 cases^[45] in comparison with 60-104 cases for LPD^[6,46].

Virtual reality participation effectively trains the novice robotic surgeon in basic surgical skills. In a recent RCT, 20 surgical trainees and 20 medical students were randomised to either laparoscopic or robotic training. They performed 6 h of training on the simulator and box trainer, and then the following day performed three surgical tasks on cadavers. Videos were recorded and analysed for time to complete, global rating score and suture errors. The robotic group consistently performed better than the laparoscopic group, with higher scores for each task and fewer suture errors^[44]. In the US, where more surgical trainees have proportionately had robotic simulation exposure than the UK and Ireland, over 90% of trainees go on to perform more than 15 general surgical procedures as a console surgeon compared with only 3% of UK trainees^[47].

Procedural-specific training has also been shown to be effective. A Dutch pancreatic cancer group was trained using the Pittsburgh five-step technique. In its first 275 cases, it had excellent operative outcomes, with minimal blood loss, a conversion rate of 6.5% and a pancreatic fistula rate of 23.6%^[11]. This RPD training protocol has also been safely implemented in Japan^[48].

The Pittsburgh group analysed its RPD cases over a nine-year period, with three phases of surgeons: (1) those with no mentorship or curriculum; (2) those with mentorship but no curriculum; and (3) those with mentorship who underwent the robotic curriculum. The surgeons in the third category, despite having performed fewer operations, had shorter operative times, with less blood loss, lower transfusion rate, fewer complications and a shorter length of hospital stay^[49].

Despite these examples, more data are required to address the optimal metric for the assessment of the minimum number of cases needed to accomplish competency and acceptable outcomes. We would advocate routine and regular video assessment of procedures to demonstrate surgical proficiency in addition to patient outcome analysis. Multi-institutional, international registries are good sources of data and participation should be encouraged.

Machine learning in robotic training

Artificial intelligence (AI) can be defined as the development of computer systems to be able to perform tasks that normally require human intelligence. Machine learning (ML) is a subset of AI in which computer systems can learn and adapt using statistical models to analyse data patterns^[50]. The applications of both AI and ML are exponentially increasing in medicine, yet their use in surgery is still in its infancy. However, the arrival of more complex algorithms and higher-powered computing has recently allowed for an increase in the use of ML in surgery^[51,52], and ML is expected to revolutionise the operating theatre and surgical training. The increasingly widespread use of MIS and robotic platforms in surgery has the potential to provide a rich dataset of surgical videos for analysis. However, the challenges of applying ML algorithms to surgical video analytics are worth noting and have limited their effective use to date^[53]. There is variability in image quality, movement and smoke artefacts, and changing objects within the visual field and anatomical structures are not clearly visualised; they lie within and are covered by other tissues. Despite these inherent difficulties, more recently, groups have evaluated the use of ML algorithms in surgery with encouraging results. However, with small datasets, the accuracy of current algorithms must be interpreted with caution. Standardising robotic training and robotic procedures will reduce some of this intra-operative variability, thus enhancing the accuracy of ML tools. The use of automated video analytics can improve surgical education and enable self-directed learning both within and outside the operating room. The ethics of using surgical videos for data analysis and the creation of ML algorithms remain an important issue for discussion by international surgical bodies. Data protection laws provide a framework to prevent the misuse of data by healthcare providers and technology companies, but with the continued evolution of AI in surgery, these regulatory organisations must adapt to ensure that collaborations between surgeons and the industry gain appropriate patient consent.

The groundwork for ML for operative interpretation has been surgical phase recognition. In this task, a dataset of MIS operative videos is input into the system that is being trained. Experienced surgeons annotate these videos with the operative phase or procedural step. These videos are then input as another dataset known as labelled training data to create the ML model. The created model aims to automatically assign the surgical phase in further operative videos^[54]. The more data the model receives, the more accurate the created algorithm. Most work published to date has looked at distinct operative phases during laparoscopic cholecystectomy, given that there are several large video datasets available to access^[55]. Jin *et al.* created an ML algorithm after analysing 107 cholecystectomy videos. This successfully assigned the seven operative steps of the procedure with 92.4% accuracy^[56]. Other researchers have similarly created algorithms that have correctly recognised the surgical phases in sleeve gastrectomy (mean accuracy 82% ± 4%)^[57], cataract surgery (mean accuracy 96.5%)^[58], laparoscopic sigmoidectomy (mean accuracy 91.9%)^[59] and endoscopic myotomy [mean accuracy 87.6% (95%CI: 87.4%-87.9%)]^[60]. By combining automated surgical phase recognition and the routine recording of an individual surgeon or trainee's procedures, operative efficiency and constructive

self-criticism can be interpreted quickly. This may improve the time taken to acquire expert procedural skills. It will also facilitate the attainment of educational tools for future surgeons.

Another application of ML in video analytics is surgical instrument recognition. The instrument used during an operation provides a guide for which procedural step or action is underway^[61]. Algorithms created by analysing laparoscopic gastrectomy found that 14 different surgical instruments could be classified with an accuracy of 83.75%^[62]. ML applications were similarly able to recognise the surgical tool used during MIS colorectal resections^[62]. Instrument recognition allows for instrument tracking, leading to automated gesture and error identification. This application is particularly important as a potential assessment of surgical expertise and skill^[63]. When using ML algorithms to analyse and track instrument motion from surgical videos, surgical expertise was predicted with an accuracy of 83%, using the Objective Structured Assessment of Technical Skills and Global Evaluative Assessment of Robotic Skills scores as the standard^[64]. Deep learning neural networks trained on videos of MIS suturing could also classify a surgeon's suturing proficiency with an accuracy of over 80%^[64]. These models constitute the starting point for the autonomous assessment of surgical competence. Similarly, computer vision models trained on over 2000 live robotic suturing videos could accurately identify the presence and type of suturing gesture (area under the curve 0.88 and 0.87, respectively)^[65]. This may be the start of autonomous robotic suturing, an area of surgery that may well transform the traditional concept of operating and surgical training.

Another novel and exciting application of ML in surgery is anatomical landmark recognition. A deep learning model was trained to identify safe and unsafe zones of dissection in laparoscopic cholecystectomies with an accuracy of 0.94 and 0.95^[66]. The models could also produce a dynamic overlay of the zones onto surgical videos. Similarly, deep artificial neural networks were created that can assess the achievement of the critical view of safety during cholecystectomy before ligation^[67]. Taking this one step further, the Institute of Image-guided Surgery of Strasbourg, France, has used real-time intra-operative augmented reality feedback during cholecystectomy, highlighting the cystic duct and cystic artery. Expanding on these algorithms, there is the potential to provide intra-operative augmented reality feedback to surgeons, particularly trainees, thereby enabling decision support and enhancing patient safety. This future application may well result in a real-time dynamic overlay of anatomy during the majority of robotic procedures.

Discrepancies in the technical abilities of surgeons are well established, and we know that higher proficiency scores, assessed using video analysis, reduce patient morbidity^[68]. Robotic surgery allows for an increasing number of objective performance metrics^[69,70], which, combined with ML algorithms, could be used as automated surgical assessment tools in the future.

SUMMARY

Robotic surgery is rapidly expanding across surgical specialties. While it remains a low-volume technique in pancreatic surgery, involvement in focused training programmes is recommended to enable surgeons to master skills prior to independent operating. Training should be standardised to ensure the attainment of assessment benchmarks and should include virtual simulation basic training in addition to procedural-specific training. Exposure to basic robotic training should be implemented in the early postgraduate years. Procedural techniques should be standardised to improve patient safety, theatre efficiency and the continuation of robotic practice. Centres undertaking MIS pancreatic resections should consider the implementation of dedicated team training and perform at least 20 robotic pancreatic resections per year. Auditing outcomes for quality assurance and participation in MIS HPB international registries are advocated. With the advance of robotic surgery and availability of surgical video datasets, ML in surgery may rapidly increase. Combined ML applications and real-time dynamic augmented reality overlays will

help to hasten the surgical learning curve, reducing the time needed to reach proficiency in training in addition to altering trainee competency assessment. Ultimately, and importantly, it will also improve patient safety.

DECLARATIONS

Authors' contributions

Made substantial contributions to research and writing of the paper: Body S, Kawka M, Gall TMH

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All authors declared that there are no conflicts of interest.

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Not applicable.

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