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Review

Applications of Artificial Intelligence in Minimally Invasive Surgery Training: A Scoping Review

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Abstract: Background/Objectives: Among the scientific literature, the significant potential of the application of artificial intelligence (AI) in minimally invasive surgery (MIS) stands out. The aim of this study is to provide a comprehensive review to analyze the scientific literature on AI applications in MIS training, selecting the main applications, limitations, opportunities and challenges in this field of research. Methods/Design: A literature search was conducted in scientific databases. The search was performed with titles or abstracts, using keywords. First, studies unrelated to the topic of study were eliminated. Next, the selection was limited to articles in English. The exclusion criteria for the search were reviews, letters, case reports, industrial articles and conference abstracts. Next, only studies published in the last ten years (2014–2024) were evaluated, with priority given to publications in the last five years (2019–2024) in surgical training in AI and MIS. Finally, the full text was reviewed to add or exclude the study from this review. Results: Of the 54 studies included in this review, 18 studies were related to skills assessment, 30 studies analyzed aspects of surgical training itself, 12 studies were related to learning aspects of surgical planning, 7 studies were based on gesture recognition and 3 studies were based on surgical action recognition to measure surgical performance during MIS training. A brief description of the main AI techniques was included in this review. Conclusions: The application of AI in MIS surgical training is still a developing field of research, which presents great potential for exploring future applications, challenges, opportunities and drawbacks, as well as synergies between the technical and clinical research fields.

Keywords: minimally invasive surgery; artificial intelligence; surgical training; skills assessment; recognition of gestures; surgical tasks

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1. Introduction

Minimally invasive surgery (MIS) has grown rapidly over the past decades and numerous minimally invasive procedures have become standard surgical techniques for some specialties [1]. The advantages of MIS for patients are widely known, and they have been clearly presented in the scientific literature [2]. These include reduction in tissue trauma, reduction in postoperative pain, faster recovery times or reduction in complications derived from surgical procedures [2]. However, MIS procedures have some limitations for surgeons that need to be addressed, such as potential ergonomic deficiencies during long surgeries, high stress levels in certain procedures or a very demanding extensive learning curve [3], which are hazardous to the surgeon's health and have a great impact on the

quality of surgical procedures and patient care [4]. Thus, laparoscopic procedures are often technically demanding, with an extensive learning curve [5]. Consequently, additional and in-depth training is required for this type of surgical technique [6].

Traditionally, novice surgeons follow a training process under the supervision of expert surgeons, which allows them to evaluate their learning [7]. The first steps consist of the visualization of the different MIS techniques performed by expert surgeons. Subsequently, novice surgeons are assigned to train on simulators with different basic tasks, such as cutting, dissection, needle handling or suturing. For this purpose, several physical, virtual and hybrid laparoscopic training simulators have been developed. The difficulty of these tasks is gradually increased until the novice surgeon acquires an adequate level of basic surgical skills [8]. Then, novice surgeons begin to participate in different surgical procedures until they reach a certain level of adequate surgical competence [9].

On the other hand, the application of artificial intelligence (AI) has exponentially grown in its use and development. These algorithms are based on non-trivial processes for discovering potentially useful knowledge initially hidden in the data [10]. Among the different AI techniques, there are several algorithms that allow the development of predictive models, which can be linear or nonlinear [11], and classification models, which can be supervised or non-supervised [12]. These models should not be confused with machine learning models that are linked to artificial neural networks (ANNs) and convolutional neural networks (CNNs), and deep learning models (DLMs), which can evaluate the results of previous predictive models and learn from these results [13]. In recent years, the apparition of a new AI technology, generative AI based on large language models (LLMs), has allowed the development of several new AI applications across various industries [14], generating a new era of AI with unbelievable potential for establishing new opportunities, limitations and challenges, since generative AI continues to evolve.

Consequently, there are many studies about AI applications in numerous research fields such as food technology [15], mathematics [16], civil engineering [17] military applications [18] or architecture [19]. Specifically, MIS is one of the medical specialties that generates very large datasets that can be processed in detail and depth by AI. Those datasets can include pre-operative datasets (clinical history, laboratory tests and imaging tests of the patients), intra-operative datasets (based on video recordings and wearable devices) and post-operative datasets (mortality, recovery process and patient outcomes). Although there is a substantial interest in AI applied to clinical data, its clinical implementation still faces obstacles due to some drawbacks, such as the following: the performance of AI models is still not perfect since it depends on the quantity and variety of the available data [20]. A lack of external validation in most of the reported studies provides additional unexpected errors [21]. The interpretability of DLM algorithms and their working principles is very difficult to understand for non-experts, especially surgeons, and generates distrust [22]. In this sense, the use of explainable AI (xAI) has grown to be interpretable to surgeons [22].

To our knowledge, there are only a few reviews focused on the applications of AI in MIS [23–29]. However, there is no general review focusing on the application of AI during surgical training in MIS. For this reason, a scoping review was conducted to systematically map the research conducted in this area. Accordingly, the following research question was formulated: what are the main applications, limitations, opportunities and challenges of AI for assistance in MIS training?

Therefore, the main objective of this study is to provide a comprehensive review to analyze the published literature on AI applications in MIS training, selecting the main applications, limitations, opportunities, challenges and existing gaps in the knowledge in this field of research.

2. Materials and Methods

2.1. Search Strategy

In November 2024, a search of the scientific literature was conducted in the PubMed, Web of Science, Scopus and IEEExplore databases. The search included observational, randomized and non-randomized studies (3486 studies). The search was performed with titles or abstracts, using keywords and hot topics and Boolean operators as follows: (artificial intelligence OR AI OR deep learning OR machine learning OR CNN OR neural networks) AND (minimally invasive surgery OR MIS OR robot-assisted surgery OR RAS) AND (surgical training OR skill assessment OR gesture recognition). In a first scoping review, we eliminated some studies outside the study topic (2426 studies). Then, the selection was limited to English-language articles (2327 studies) with an abstract, published in peer-reviewed journals. The search was complemented by checking published reviews and their references (2327 studies). The exclusion criteria for the search were reviews, letters, case reports, industrial papers and conference abstracts (727 studies). Next, only studies published in the last ten years (2014–2024) were evaluated, with priority given to publications in the last five years (2019–2024) in artificial intelligence and surgical training (613 studies).

Once the search was completed, we screened by title and abstract (64 studies). Subsequently, the full text was reviewed to add or exclude the study from this review (54 studies). Once the full text was added, data from the studies were extracted and analyzed. To increase consistency among reviewers, two authors (D.C. and M.J.P.-S.) screened the full text of all the studies, and the remaining two authors (J.A.S.-M. and F.M.S.-M.) reviewed and amended the screening and data extraction manually for this review. After that, all authors resolved, in the case that it is needed, possible disagreements on study selection and data extraction by consensus and discussions. This method of data identification and assessment conformed to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 statement and checklist that shown in Table S1 [30]. The final protocol was registered prospectively with the Open Science Framework on 20 December 2024 (osf.io/mca3y). Figure 1 shows the flow diagram of the study selection.

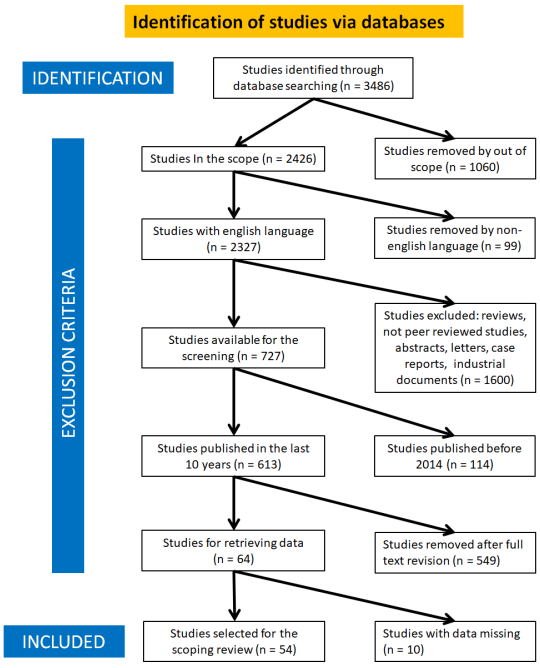


Figure 1. Flow chart of the condition selection for the studies of the presented scoping review.

2.2. Analysis of Studies

Since the studies were focused on different application domains in MIS training, five different application groups were created: (i) skills assessment, (ii) surgical training, (iii) surgical planning, (iv) surgical gesture recognition, and (v) surgical action detection. Each study was assigned to the corresponding application groups, and each study could belong to one group or more than one group. For each group, a table was prepared to visually analyze the data of the studies. For this review study, all sources of information included in the synthesis phase will be considered equally.

For each table, the Sample, Phenomenon of Interest, Design, Evaluation, and Type of Investigation (SPIDER) tool [31] was applied. The SPIDER tool reports: the dataset with the number of surgeons and procedures (sample), the type of tasks or procedures (phenomenon of interest), the application, robotic platform, AI algorithms and input data (design), the results obtained (evaluation) and the objectives of the studies (research). For that, a data extraction form was developed and created by all authors in a consensus manner to determine which variables to extract. Two authors (D.C. and M.J.P.-S.) extracted the data for all studies independently and the remaining two authors (J.A.S.-M. and F.M.S.-M.) reviewed and amended the data extraction manually, discussed the results and continuously updated the data extraction form in an iterative process for this review.

2.3. Evaluation of the Scope Throughout the Years

Analyzing the studies published in this field, an increasing number of publications has been observed in recent years, from about 10 publications between 2000 and 2019 to 36 publications in 2020, 70 publications in 2021, about 100 publications in 2022 and 2023, and 260 publications in 2024. This fact demonstrates a growing interest in AI applications, specifically in surgical training. Figure 2 shows the publications per year between 2000 and 2024, indicating an increasing number of publications from 2020 onwards.

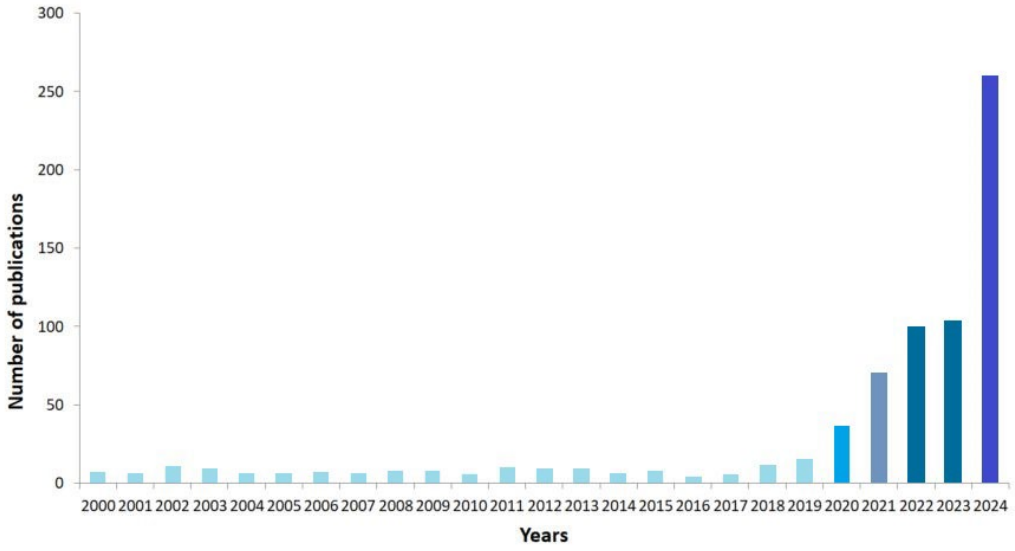


Figure 2. Evolution of the number of publications in the applications of AI in surgical training in the last 25 years (2000–2024).

3. Results and Discussion

The 54 studies included in this review comprise 18 studies related to skills assessment during surgical training, 30 studies related to aspects of surgical training itself, 12 studies related to aspects of learning surgical planning, 7 studies on gesture recognition and its improvement during surgical training, and 3 studies on recognition of surgical actions to

measure surgical performance during surgical training. This set of studies is presented in different Tables (Table 1 for skills assessment, Table 2 for surgical training, Table 3 for surgical planning, Table 4 for gesture recognition and Table 5 for surgical action recognition). In addition, a summary of the AI algorithms applied in the studies included in this scoping review has been added.

3.1. Artificial Intelligence Techniques

In this section, a summary of the AI algorithms used in the analyzed studies of this scoping review is described to aid in their understanding and main purposes.

- AdaBoost: this technique is an unsupervised statistical classification algorithm that can be used in conjunction with other types of learning algorithms to improve their performance by providing a boosted classifier [32].
- ANN: This is an AI technique that attempts to simulate the performance of a human brain. In this way, the generated predictive model will continue to learn based on the values of the signals generated in the neural network [10].
- Autoencoder: This algorithm is a type of ANN that is applied to unsupervised learning. This algorithm is based on the principle of the encoding and decoding process. It is usually applied for the classification of unlabeled data [33].
- Clustering: this is an algorithm that consists of positioning the log data in several non-overlapping clusters or groups so that the data log is placed at the smallest possible Euclidean distance from the centroids of the different clusters [34].
- CNN: This AI algorithm is a regularized type of feed-forward ANN that learns from the features by itself using an optimization kernel. This type of ANN has been applied to process predictive models from many different types of multimedia data [35].
- Decision tree (DT): This is a decision modeling tool that graphically displays the classification process of a given input for a given output class label. This method is one of the learning algorithms that generate classification models in the form of tree structures [36].
- DLM: These methods are an evolution of machine learning, which focuses on learning from the results extracted from an ANN. This type of AI technique is performed in tasks such as classification (supervised, semi-supervised and unsupervised), prediction and learning representation [35].
- Edge detection: It is a computer vision method to identify edges, curves in digital images or discontinuities in signal processing. It is a fundamental tool for research in fields such as image processing, computer vision or feature detection and extraction [37]. This technique has been enhanced by AI.
- Fuzzy rules: this method is used in fuzzy logic systems to infer an output from independent input variables [38].
- Generative adversarial network (GAN): This method is a class of ANNs or DLMs, generally used as an approach framework for generative AI. This method is composed of two ANNs, where one ANN wins when another ANN loses [39].
- Image segmentation: This is a computer vision technique to discriminate discrete groups of pixels in a digital image to inform object detection. Complex visual data are being analyzed by applying AI to image segmentation [37].
- K-nearest neighbors (KNN): This is a supervised learning method typically used for classification purposes. The result is a group of classes with components of similar characteristics [40].
- LLM: This is a type of AI computational model designed for natural language processing tasks closely related to generative AI. This model acquires the capabilities by

learning statistical relations from a large amount of text for a semi-supervised training process [41].

- Linear regression (LR): This is a predictive technique that allows the creating of future models that can be predicted from current data by trend analysis. This method shows a linear relationship between a dependent variable and several independent variables [42].
- Naive Bayes: This is an AI algorithm for supervised classification based on Bayesian principles and probability theory [43]. This algorithm can be fed by an ANN.
- Partial least squares (PLS): this method is a predictive technique based on the statistical relationship between principal component analysis and a reduced rank regression, finding a linear regression model that projects the predicted and observable variables to a new space with maximum covariance [44].
- Principal component analysis (PCA): This is an exploratory data analysis technique used for data visualization and processing based on linear dimensionality reduction. It can also be used for supervised classification [45].
- Random forest (RF): This is an ensemble learning technique used for classification and regression. This technique is based on the use of multiple DTs to obtain a correct result. This method is one of the learning algorithms that generate classification models in the form of tree structures [36].
- Support vector machine (SVM): this method performs a nonlinear predictive approximation, representing a desirable nonlinear relationship that minimizes the separation by tolerating a small error in fitting the data in the transformed space [46].

3.2. Skills Assessment Applications

In this section, 18 studies focused on the evaluation of surgeon skills during surgical training were analyzed (Table 1). Regarding the surgical tasks used, nine of them referred to basic surgical training tasks such as knot tying, needle passing and suturing, seven to training using virtual reality (VR) simulators and two to simulations of colorectal surgeries in phantom models. As for the input data, twelve of them used video frames, nine applied data from wearable devices, one used image data, and one used eye tracking and a subjective survey. Regarding the platform used for surgical training, eleven studies used the da Vinci^{TM} surgical robotic system (Intuitive Surgical, Sunnyvale, CA, USA), three studies included different simulators, two studies analyzed the data from conventional laparoscopic surgeries, one study used an experimental robotic surgical system and one a percutaneous guided system. Several AI algorithms were applied in these 18 studies: ANN, autoencoder, CNN, DT, fuzzy rules, KNN, LR, Naive Bayes, PCA and SVM; all these algorithms are described in Section 3.1.

Table 1. Studies on the application of AI in surgical training for competency assessment.

Authors and Year	Number of Surgeons	Number of Surgical Procedures	Type of Surgical Tasks	Input Data	Robotic Platform/Conventional Surgery	AI Algorithms
Alonso-Silveiro et al., 2018 [47]	16	400	VR simulator	Image data	Conventional laparoscopy surgery	ANN [1]
Azimi et al., 2018 [48]	3	3	VR simulator	Wearable device data	Neurosurgery simulator	CNN [1]
Dublin et al., 2018 [49]	14	28	VR simulator	Wearable device data	da Vinci^{TM} surgical system	LR [1]
Fard et al., 2018 [50]	8	48	Knot tying and suturing	Wearable device data and video frames	da Vinci^{TM} surgical system	KNN [1], LR [1], and SVM [1]

Table 1. *Cont.*

Authors and Year	Number of Surgeons	Number of Surgical Procedures	Type of Surgical Tasks	Input Data	Robotic Platform/Conventional Surgery	AI Algorithms
Wang and Fey, 2018 [51]	8	72	Knot tying, suturing, and needle passing	Wearable device data and video frames	da Vinci™ surgical system	CNN [1]
Zia and Essa, 2018 [52]	8	72	Knot tying, suturing, and needle passing	Wearable device data and video frames	da Vinci™ surgical system	KNN [1], PCA [1], and SVM [1]
Ershad et al., 2019 [53]	14	28	VR simulator	Wearable device data	da Vinci™ surgical system	SVM [1]
Fawaz et al., 2019 [54]	11	99	Knot tying, suturing, and needle passing	Wearable device data and video frames	da Vinci™ surgical system	CNN [1]
Funke et al., 2019 [55]	9	81	Knot tying, suturing, and needle passing	Video frames	da Vinci™ surgical system	CNN [1]
Holden et al., 2019 [56]	24	43	Needle passing and US probe motion	Video frames	Percutaneous guided interventions	DT [1] and fuzzy rules
Tan et al., 2019 [57]	16	27	VR simulator	Video frames	Simulator VREP	CNN [1]
Khalid et al., 2020 [58]	8	120	Knot tying, suturing, and needle passing	Video frames	da Vinci™ surgical system	Autoencoder
Wu et al., 2020 [59]	8	180	Endowrist manipulation, clutching, needle control, needle driving, peg transfer and suturing	Eye-tracking metrics and subjective surveys	da Vinci™ surgical system	Naive Bayes
Zhang et al., 2020 [60]	8	552	Knot tying, suturing, and needle passing	Wearable device data and video frames	Experimental microsurgical robot research platform	CNN[1]
Shedage et al., 2021 [9]	33	66	VR simulator	Wearable device data	VATDEP Simulator	KNN [1], LR [1], and SVM [1]
Reich et al., 2022 [61]	21	83	VR simulator	Video frames	Conventional laparoscopy surgery	ANN [1]
Gillani et al., 2024 [62]	10	461	Colorectal surgeries	Video frames	da Vinci™ surgical system	LR [1]
Gillani et al., 2024 [63]	10	461	Colorectal surgeries	Video frames	da Vinci™ surgical system	LR [1]

[1] ANN: artificial neural network. CNN: convolutional neural network. DT: decision tree. KNN: k-nearest neighbors. LR: linear regression. PCA: principal component analysis. SVM: support vector machine.

Several of these studies used the John Hopkins University Intuitive Gesture and Surgical Skills Assessment Work Set (JIGSAWS) [64] to conduct skills assessments during surgical training. The JIGSAWS includes three basic surgical tasks: knot tying, needle passing and suturing, which must be completed three to five times by at least eight surgeons [64]. This fact generates an evident homogeneity in some results. Thus, surgeons in studies using JIGSAWS achieved an accuracy between 0.774 and 1, using AI techniques such as KNN and SVM [50,52]. On the other hand, the results vary between 0.992 and 1 when the AI technique applied was CNN [51,54,55,58,60]. However, although the results obtained are very positive, JIGSAWS has some drawbacks such as the following: the limitation of only three basic surgical tasks, not including other basic fundamental tasks such as dissection; the number of surgeons in each attempt also being limited to between eight and fourteen; and that at most surgeons can repeat each task five times, a fact that is strictly limiting

for a novice surgeon in the learning phase. In contrast to these limitations, Wu et al. [59] analyzed 15 robotic skill sessions for a total of 180 surgical tasks performed by 8 surgeons. To assess the surgeons' skill during training, they used eye tracking, achieving a correlation degree of 0.51 and predicting workload levels with an accuracy of 0.847 [59].

In the case of the use of VR simulators, some studies [47,61] achieved an accuracy between 0.83 and 0.93 in the assessment of surgical skills using ANN, showing its potential to be applied in possible surgical training programs. Similarly, Dublin et al. [49] obtained similar results to those of the ANN studies. In this case, they employed LR algorithms with lower complexity, improving the quality of the training process and preparing novice surgeons for the evaluation of new and difficult skills. Other studies using VR for surgical training [48,53,57] presented less favorable results using CNN and SVM but offered powerful audio-visual feedback and assistance during training. In addition, these training systems can enhance the real-time view of VR and allow augmentation of the training process for surgeons. Finally, these systems allow a high versatility in customizing the training style, thus adapting to the trainee's learning curve.

Holden et al. [56], who presented a study for surgical training assistance in percutaneous guided surgery, obtained excellent results applying fuzzy rules and DTs. They achieved more useful feedback for the trainees using DTs than with fuzzy rules. This feedback proved useful in supporting self-guided training in interventions using these two AI techniques.

Giliani et al. [62,63] evaluated the skills of novice (<50 h of MIS experience), intermediate (50 to 100 h of MIS experience) and expert (>100 h of MIS experience) surgeons in 461 specific MIS steps with the aim of objectively and automatically classifying their level of experience. In both studies, novice surgeons showed less speed and acceleration in surgical movements, which allowed the differentiating of the group of expert surgeons from intermediate and novice surgeons. The automation of this evaluation process could objectively provide self-feedback to surgeons in training and show scalable metrics on the training process until a certain level of surgical proficiency is reached, regardless of the hours in surgeries performed.

3.3. Surgical Training Application

In this section, thirty studies were analyzed (Table 2). Regarding surgical tasks, eight of them included knot tying, needle passing and suturing. Regarding surgical specialty, seven studies focused on the specialty of urology, six studies used VR simulators and four used colorectal surgery simulators in phantom models. Regarding input data, eighteen studies used video stills, eleven used data from wearable devices, six used image data, and one used eye tracking and a subjective survey. Regarding the platform used for surgical training, seventeen of them used the da Vinci^{TM} surgical system, six of them used conventional laparoscopic surgery, three of them used the Versius^{TM} surgical system, three of them performed conventional MIS in different specialties (pulmonary, neurology and arthroscopy), two of them used different simulators, one of them performed the MICS-MVR surgical system and the other used a percutaneous guided system. Several AI algorithms were applied in these studies: AdaBoost, ANN, clustering, CNN, DLM, DT, fuzzy rules, GAN, image segmentation, KNN, LR, Naive Bayes, PCA, PLS, RF and SVM; all these algorithms are described in Section 3.1.

Table 2. Studies about AI and surgical training with surgical training application.

Authors and Year	Number of Surgeons	Number of Surgical Procedures	Type of Surgical Tasks	Input Data	Robotic Platform/Conventional Surgery	AI Algorithms
Nosrati et al., 2016 [65]	97	3096	Urology surgeries	Image data	da Vinci™ surgical system	ANN [1], LR [1] and RF [1]
Krishnan et al., 2017 [66]	5	77	Circle cutting, needle passing and peg transfer	Wearable device data and video frames	da Vinci™ surgical system	clustering
Sarikaya et al., 2017 [67]	10	2455	Ball placement, peg transfer, suturing, knot tying, needle passing, labyrinth, and urology and colorectal surgery	Video frames	da Vinci™ surgical system	CNN [1]
Zia et al., 2017 [68]	9	225	Two hand suturing, uterine horn dissection, suspensory ligament dissection, rectal artery skeletonization and rectal artery clipping	Wearable device data and Video frames	da Vinci™ surgical system	ANN [1] and clustering
Dubin et al., 2018 [49]	14	28	VR simulator	Wearable device data	da Vinci™ surgical system	LR [1]
Ross et al., 2018 [69]	21	23,000	Urology and colorectal surgery	Image data and video frames	da Vinci™ surgical system	CNN [1] and GAN [1]
Shafiei et al., 2018 [70]	3	170	Urology surgery	Image data	da Vinci™ surgical system	PCA [1] and SVM [1]
Colleoni et al., 2019 [71]	18	500	Urology and colorectal surgery	Video frames	da Vinci™ surgical system	CNN [1]
Engelhardt et al., 2019 [72]	9	90	Surgeries on silicone model	Video frames	MICS-MVR surgical system	GAN [1]
Ershad et al., 2019 [53]	14	28	VR simulator	Wearable device data	da Vinci™ surgical system	SVM [1]
Holden et al., 2019 [56]	24	43	Needle passing and US probe motion	Video frames	Percutaneous guided interventions	DT [1] and fuzzy rules
Islam et al., 2019 [73]	8	225	Surgeries on porcine model	Video frames	da Vinci™ surgical system	GAN [1]
Tan et al., 2019 [57]	16	27	VR simulator	Video frames	Simulator VREP	CNN [1]
Attanasio et al., 2020 [74]	6	1080	Neurology surgery	Video frames	da Vinci™ surgical system	CNN [1]
Liu et al., 2020 [75]	10	2455	Ball placement, peg transfer, suturing, knot tying, needle passing, labyrinth, and urology and colorectal surgery	Video frames	da Vinci™ surgical system	CNN [1]
Wu et al., 2020 [59]	8	180	EndoWrist manipulation, clutching, needle control, needle driving, peg transfer and suturing	Eye-tracking metrics and subjective surveys	da Vinci™ surgical system	Naive Bayes
De Boer et al., 2021 [76]	9	32	Urology surgeries	Wearable device data	Conventional urology surgeries	LR [1] and PLS [1]
Chen et al., 2021 [77]	17	68	Urology surgery	Wearable device data	da Vinci™ surgical system	AdaBoost and RF [1]
Shedage et al., 2021 [9]	33	66	VR simulator	Wearable device data	VATDEP Simulator	KNN [1], LR [1] and SVM [1]
Reich et al., 2022 [61]	21	83	VR simulator	Video frames	Conventional laparoscopic surgery	ANN [1]
Ayuso et al., 2023 [78]	16	10,514	Colorectal surgeries	Image data and video frames	Conventional laparoscopic surgery	CNN [1], DLM [1], and GAN [1]
Moglia et al., 2023 [79]	176	352	VR simulator	Wearable device data	da Vinci™ surgical system	CNN [1]
Mohamadipanah et al., 2023 [80]	6	4997	Pulmonary surgeries	Video frames	Conventional pulmonary surgeries	GAN [1]

Table 2. *Cont.*

Authors and Year	Number of Surgeons	Number of Surgical Procedures	Type of Surgical Tasks	Input Data	Robotic Platform/Conventional Surgery	AI Algorithms
Caballero et al., 2024 [81]	11	27	Suturing, needle passing, dissection, labyrinth, general surgery, urology and gynecology	Wearable device data	Versius™ surgical system and conventional laparoscopic surgery	ANN [1], LR [1] and SVM [1]
Gillani et al., 2024 [62]	10	461	Colorectal surgeries	Video frames	da Vinci™ surgical system	LR [1]
Gillani et al., 2024 [63]	10	461	Colorectal surgeries	Video frames	da Vinci™ surgical system	LR [1]
Gruter et al., 2024 [82]	36	216	Colorectal surgeries	Video frames	Conventional laparoscopic surgery	Image segmentation
Orgiu et al., 2024 [83]	6	20	Arthroscopy surgeries	Image data and video frames	Conventional arthroscopy surgeries	CNN [1]
Pérez-Salazar et al., 2024 [8]	6	18	Suturing	Wearable device data	Versius™ surgical system and conventional laparoscopy surgery	LR [1]
Pérez-Salazar et al., 2024 [84]	7	42	Peg transfer, cutting, needle passing and suturing	Wearable device data	Versius™ surgical system and conventional laparoscopy surgery	ANN [1] and LR [1]

[1] ANN: artificial neural network. CNN: convolutional neural network. DLM: deep learning method. DT: decision tree. GAN: Generative adversarial network. KNN: k-nearest neighbors. LR: linear regression. PCA: principal component analysis. PLS: partial least square. RF: random forest. SVM: support vector machine.

Nosrati et al. [65] developed a new preoperative endoscopic technique to detect visible and occluded structures in surgical training. The training of AI techniques (ANN, LR and RF) was performed with only 15 clinical cases and an improvement of over 45% compared to the state-of-the-art mean results was obtained. This study demonstrated the potential of VR for MIS surgical training. Attanasio et al. [69,71,75] used CNN in video frames from urology and colorectal surgery training to reduce annotation effort, improving performance by 75% and accuracy to between 0.851 and 0.954. Attanasio et al. [74] applied CNN to improve training in neurological surgery, improving by at least 25% in experimental validation with respect to the mean of the state of the art. The framework proposed by Attanasio et al. [74] could be applied to a wide range of surgical tasks. On the other hand, using VR, some studies [49,53] demonstrated better LR performance than the multivariate model, improving the surgical training process, reducing time and costs and completing more surgical tasks. Thus, Tan et al. [57] provided deep learning by reinforcement to give a demonstration of high-quality learning in surgical training. Reich et al. and Moglia et al. [61,79] applied ANN and CNN models and obtained an accuracy of 0.833. This demonstrates the potential of ANNs and CNNs to understand the level of surgical expertise, contributing to the shift towards advanced task-based competence in surgical training [61].

Holden et al. [56] applied AI-based solutions for surgical training on percutaneous guided surgery and obtained excellent results applying fuzzy rules and DT. They achieved more useful feedback using DTs than fuzzy rules. Similarly, some studies tested the evaluation of self-guided percutaneous interventions with unsupervised algorithms [66,76], highlighting the use of LR, PLS and clustering as AI techniques.

Surikaya et al. [67] studied the detection of surgical tools in endoscopic videos during surgical training. In this study, the average accuracy was 91% for six different surgical tasks, improving the results obtained for JIGSAWS [64]. For the detection of surgical activities, Zia et al. [68] applied clustering to their recognition, analyzing training procedures to improve the most relevant steps of the different surgical tasks in MIS training.

Shafiei et al. [70] measured mutual trust in MIS procedures among the surgical team, and between the surgical team and the patient. Ayuso et al. [78] showed the potential of

GANs and DLMs to improve surgical training tasks in the specialty of urology. In this study, the GAN achieved an accuracy higher than 0.59 with an error lower than 0.056 [78].

Some studies [72,73] obtained an improvement in visualization on a 3D monitor over the baseline method (93% improving the baseline method, with depth perception and realism) during surgical training. This model improved existing algorithms for surgical tool segmentation and prediction and segmentation accuracy. On the other hand, Gruter et al. [82] achieved a high accuracy of between 0.885 and 0.945 in that study, highlighting the potential of evaluation in colorectal surgery training using video endoscope analysis.

Wu et al. [59] used eye-tracking metrics to detect workload during MIS tasks to prevent workload in the performance of surgical tasks. These metrics can potentially be used to identify tasks with high workloads and provide measures for assisting surgical training in MIS, avoiding high levels of elevated stress and improving the quality of surgical procedures.

Mohamadipanah et al. [80] evaluated more than 4900 video frames in order to improve the evaluation and training process in pulmonary MIS. For this purpose, a GAN was applied as an AI technique that makes up for the lack of data on events that may occur during lung surgery, improving the quality of training and identifying new surgical strategies that had not been previously evaluated.

Orgiu et al. [83] evaluated CNN applications for the recognition of bony structures in assistance during wrist arthroscopy training. This study presented some limitations, as some bones were detected more accurately than others. This fact suggests the importance of proper training of the algorithms to improve bone detection.

Some studies [8,9,77,81,84] offer a comparison between the skill level of novice and expert surgeons during the performance of surgical training tasks such as suturing, needle passing or dissection. In particular, studies offer feedback to surgeons in order to self-assess their level of surgical competence [77] by applying AdaBoost and RFs in urological surgery training. Thus, Shedage et al. [9] evaluated surgical tasks in a VR simulator with three AI techniques (KNN, LR and SVM), obtaining an accuracy higher than 0.74. Caballero et al. [81] measured stress during surgical training to try to avoid high stress levels based on data from the EDA wearable device, applying an ANN, LR and SVM and obtaining an accuracy higher than 0.75. On the other hand, Perez-Salazar et al. [8,84] compared the performance of novice and expert surgeons during MIS surgical training using motion analysis, muscle activity and localized muscle fatigue prediction by applying an ANN and LR.

Finally, in terms of muscle activity, several studies [8,62,63,84] measured muscle activity during surgical training with the aim of predicting and avoiding musculoskeletal problems during surgery. These studies showed better performance with the dominant side than with the non-dominant side for expert surgeons and similar performance with both sides for novice surgeons [62,63]. In particular, the predictive model (ANN, LR) obtained a high accuracy (>0.75) for cutting, maze and pin transfer tasks, indicating that it can be an innovative solution for the prevention of ergonomic risk situations and for improving the quality of surgical training and future patient care [8,84].

3.4. Surgical Planning Applications

In this section, 12 studies on surgical planning training were analyzed (Table 3). Of the surgical tasks used, ten studies involved specialty urological surgery planning tasks, one study involved tasks for arthroscopic surgery training, and the remainder were used strictly for surgical planning. In terms of input data, eight studies used image data, five applied video stills, one applied data from wearable devices, and one used questions and answers via ChatGPT messages. Regarding the platforms used for surgical training, eleven

of the studies used the da Vinci™ surgical system, and the remaining study used different robotic surgical systems. Several AI algorithms were applied in these 12 studies: AdaBoost, ANN, CNN, CNN, DT, edge detection, image segmentation, KNN, LLM, LR, Naive Bayes, RF and SVM. All these algorithms are described in Section 3.1.

Table 3. Studies about AI and surgical training with surgical planning application.

Authors and Year	Number of Surgeons	Number of Surgical Procedures	Type of Surgical Tasks	Input Data	Robotic Platform/Conventional Surgery	AI Algorithms
Malpani et al., 2016 [85]	6	24	Urology surgeries	Image data	da Vinci™ surgical system	CNN [1], RF [1] and SVM [1]
Hung et al., 2018 [86]	9	78	Urology surgeries	Image data	da Vinci™ surgical system	KNN [1], LR [1], RF [1] and SVM [1]
Baghdadi et al., 2019 [87]	20	20	Surgical planning	Video frames	da Vinci™ surgical system	Edge detection and image segmentation
Hung et al., 2019 [20]	8	100	Urology surgeries	Image data	da Vinci™ surgical system	CNN [1] and RF [1]
Nakawala et al., 2019 [88]	3	9	Urology surgeries	Video frames	da Vinci™ surgical system	CNN [1]
Wong et al., 2019 [89]	7	338	Urology surgeries	Image data	da Vinci™ surgical system	KNN [1], LR [1] and RF [1]
Zhao et al., 2019 [90]	14	424	Urology surgeries	Image data	da Vinci™ surgical system	AdaBoost, ANN [1], CNN [1], DT [1], LR [1] and RF [1]
Zia et al., 2019 [91]	12	100	Urology surgeries	Image data and video frames	da Vinci™ surgical system	CNN [1]
Luongo et al., 2020 [92]	12	3002	Urology surgeries	Image data and video frames	da Vinci™ surgical system	CNN [1]
Sumitomo et al., 2020 [93]	9	400	Urology surgeries	Image data	da Vinci™ surgical system	ANN [1], CNN [1], image segmentation, Naive Bayes, RF [1] and SVM [1]
Wu et al., 2021 [94]	7	168	Urology surgeries	Wearable device data and video frames	da Vinci™ surgical system	LR [1], Naive Bayes and SVM [1]
Li et al., 2024 [95]	3	10	Arthroscopy surgeries	ChatGPT prompts	Robotic surgical systems	LLM [1]

[1] ANN: artificial neural network. CNN: convolutional neural network. DT: decision tree. KNN: k-nearest neighbors. LLM: large language models. LR: linear regression. RF: random forest. SVM: support vector machine.

Some studies [85,88,91,92] planned and predicted the main steps of surgical training in urology. For prediction, a CNN, RF and SVM were applied for the detection of the main steps during surgical planning, achieving an accuracy between 0.74 and 0.88 and a recall parameter between 0.83 and 0.98. The highest accuracy was achieved by applying the CNN. Future steps could combine this planning with monitoring of the execution of the surgical procedure during training [8,62,63,84]. These results could be compared with those obtained in a recently published study by the authors regarding the design of a planning system in percutaneous ultrasound-guided surgery [96].

Hung et al. [86] tested a surgical planner with automated surgeon performance metrics in MIS surgical training. This development allows us to solve one of the main limitations of traditional surgical training, which is to be able to customize the learning curve of surgeons. Similarly, Baghdadi et al. [87] generated an application to measure surgeon performance during the surgical planning process based on computer vision and video stills with scores above 0.833. Wu et al. [94] generated new metrics to measure surgeon performance during

surgical training. These metrics can complement the feedback of surgeons in training by adjusting to their learning curve. Zhao et al. [90] predicted surgical duration by applying different AI techniques (AdaBoost, ANN, CNN, DT, LR and RF) from the duration of different surgical training tasks, obtaining an accuracy of 0.775.

Some studies [20,89,93] described the surgical planning process during prostatectomy training using MIS and urinary contingency assessment. The accuracy achieved in these studies ranged between 0.859 and 0.976 when applying different AI techniques (ANN, CNN, image segmentation, KNN, LR, Naive Bayes, RF and SVM), which is considered a good performance. To measure urinary continence during surgical training, surgical planners from 3 to 6 months [20] and from 1 to 6 months [93] were developed, showing similar results in the preoperative stage.

Li et al. [95] used ChatGPT indications to evaluate anterior cruciate ligament (ACL) reconstruction planning. This study showed good performance (three satisfactory responses, two unsatisfactory responses and one excellent response) in ChatGPT indications during training, providing generalized information about ACL tears and reconstruction.

3.5. Recognition of Surgical Gestures Applications

In this section, seven studies on surgical gesture recognition for training applications were analyzed (Table 4). Four studies focused on the specialty of urology and three on surgical gesture recognition during surgical training. Regarding input data, five studies used video images, three used image data and three used handheld device data. As for the platforms used for surgical training, six of the studies used the da Vinci™ surgical system and the other study used the Raven II surgical system. Several AI algorithms were applied in these seven studies: ANN, clustering, CNN, KNN, PCA, RF and SVM. All these algorithms are described in Section 3.1.

Table 4. Studies about AI and surgical training with recognition of surgical gesture application.

Authors and Year	Number of Surgeons	Number of Surgical Procedures	Type of Surgical Tasks	Input Data	Robotic Platform/Conventional Surgery	AI Algorithms
Despinoy et al., 2016 [97]	3	12	Drawing R letter and peg transfer	Wearable device data and video frames	Raven II surgical system	KNN [1] and SVM [1]
Malpani et al., 2016 [85]	6	24	Urology surgeries	Image data	da Vinci™ surgical system	CNN [1], RF [1] and SVM [1]
Fard et al., 2017 [98]	8	72	Knot tying, needle passing and suturing	Wearable device data and video frames	da Vinci™ surgical system	Clustering and PCA [1]
Di Petro et al., 2019 [99]	8	80	Suturing and closure wound	Wearable device data and video frames	da Vinci™ surgical system	ANN [1] and CNN [1]
Nakawala et al., 2019 [88]	3	9	Urology surgeries	Video frames	da Vinci™ surgical system	CNN [1]
Zia et al., 2019 [91]	12	100	Urology surgeries	Image data and video frames	da Vinci™ surgical system	CNN [1]
Luongo et al., 2020 [92]	12	3002	Urology surgeries	Image data and video frames	da Vinci™ surgical system	CNN [1]

[1] ANN: artificial neural network. CNN: convolutional neural network. KNN: k-nearest neighbors. PCA: principal component analysis. RF: random forest. SVM: support vector machine.

Despinoy et al. [97] compared their new automatic method with the manual annotation of surgical gestures, obtaining an accuracy of 0.974, and, during the learning process, a mean match score of 0.819 was achieved for the fully automated gesture recognition process. This system allows improvements in the efficiency of surgical training, minimizing the learning

curve. Similarly, Fard et al. [98] achieved an accuracy of 0.83 and during the learning process obtained a mean matching score of 0.77. This approach demonstrates that the proposed method can provide more information about surgical training and can contribute to the automation of MIS surgical training. Di Petro et al. [99] automated the segmentation and classification of 10 gestures by applying an ANN and CNN to provide automated and targeted evaluation and feedback during surgical training. This demonstrated the potential of ANNs and CNNs for gesture recognition during surgical training. Some studies [91,92] showed the potential of CNNs to recognize 12 surgical gestures with an accuracy of 0.85 to 0.88, demonstrating the potential of gesture recognition for the future automation of robotic surgery.

Malpani et al. [85] used advanced computer vision algorithms to extract information from images and gesture recognition, achieving an accuracy of 0.75 with respect to reality. Similarly, Nakawala et al. [88] recognized some gestures during surgical workflow training in urology. This study found that the combined use of CNNs and knowledge representations of surgical training is a promising approach for multilevel gesture recognition during surgical training.

3.6. Detection of Surgical Actions Applications

In this section, three studies on surgical action recognition were analyzed, of which two dealt with surgical action recognition during surgical training and one with colorectal surgical training with MIS (Table 5). Regarding the input data, three of the studies used video frames and one used data from wearable devices. Regarding the platform used for surgical training, the da Vinci^{TM} surgical system was used in all of them. Several AI algorithms were applied in these studies: ANN, autoencoder, clustering and LR. All these algorithms are described in Section 3.1.

Table 5. Studies about AI and surgical training with detection of surgical actions application.

Authors and Year	Number of Surgeons	Number of Surgical Procedures	Type of Surgical Tasks	Input Data	Robotic Platform/Conventional Surgery	AI Algorithms
Zia et al., 2017 [68]	9	225	Two-hand suturing, uterine horn dissection, suspensory ligament dissection, rectal artery skeletonization and rectal artery clipping	Wearable device data and Video frames	da Vinci^{TM} surgical system	ANN [1] and clustering
Khalid et al., 2020 [58]	8	120	Knot tying, suturing and needle passing	Video frames	da Vinci^{TM} surgical system	Autoencoder
Gillani et al., 2024 [62]	10	461	Colorectal surgeries	Video frames	da Vinci^{TM} surgical system	LR [1]

[1] ANN: artificial neural network. LR: linear regression.

Zia et al. [68] recognized surgical actions related to colorectal surgeries by applying an ANN and clustering as AI techniques to provide feedback on individually recognized surgical tasks to improve surgical MIS training. Khalid et al. [58] recognized several surgical actions with high accuracy (0.99 for suturing, 0.99 for tying knots and 0.91 for passing needles, with an accuracy of 0.85 for novice surgeons and 0.80 for expert surgeons) by applying the autoencoder as an AI technique. This study is the first step in creating an automatic feedback mechanism for surgeons to learn and refine their learning curve. Gilliani et al. [62] generated new LR-based objective indicators to recognize some surgical

actions during surgical training. These indicators provide automatic, objective and scalable metrics to give feedback to novice surgeons during surgical training.

4. Current Limitations, Future Challenges and Opportunities

In this scoping review, we identified 54 primary studies addressing AI applications in MIS surgical training, published between 2014 and 2024. Our findings identify the main advantages and the main limitations of AI applications in MIS surgical training. These findings were identified individually from AI and MIS points of view. Moreover, future challenges and opportunities in this field of research were also identified.

It is noteworthy that technological solutions for assisting the acquisition of skills acquired by conventional methods are booming. In this review, the scientific literature on AI applications for assisting surgical training in MIS has been evaluated. From the MIS point of view, the main drawbacks are the possible ergonomic deficiencies during long surgeries, high stress levels in certain procedures or a large and very demanding learning curve. From the AI point of view, the main drawbacks regarding the available studies are the small number of participating surgeons, the small datasets of some studies and the lack of validation in most of them. Another drawback highlighted in this review is the incompatibility between some AI processes and MIS surgical training, which does not allow the use of possible solutions. Finally, AI-based solutions may lead to potential technical failures as a consequence of the lack of properly validated solutions, which could disrupt the learning process.

Surgical MIS training generates large amounts of data, both from wearable devices and from video frames or images, which require very expensive treatments for their use in AI techniques, such as image segmentation and processing, manual annotation and supervision of clinical experts generating additional costs. The automation of these processes is key to achieving better surgical training models in the coming years, optimizing costs and improving incorrect surgical gestures, as well as postures, in real time.

It should be noted that most of the studies present in this review have a sufficient number of samples to adequately train the predictive models and provide robustness to these models to improve the quality of surgical MIS training. Another innovative solution put forward in these studies is the feedback offered to surgeons during their training process. Through these solutions, it is possible to adapt and optimize the learning curve and MIS surgical training tasks to the surgeons' needs, self-adjusting their progress to their level of experience, automating the correction of common errors and correcting the weaknesses and enhancing the strengths of these surgeons in training.

The application of innovative AI techniques to assist and improve surgical procedures during MIS learning is growing exponentially, especially through the use of virtual assistants with useful recommendations. An example of such an assistant could be new LLM-based methods such as ChatGPT 5.0, Microsoft Copilot 365, Google Gemini 1.5 Pro, Amazon Alexa 2.2.548660.0, Apple Siri 18.1, or Yahoo Artifact 1.0, which have the ability to point out common errors that occur during surgical MIS training.

The main challenges that could be extracted for this scoping review are as follows: (i) to automatically plan optimal trajectories and steps during MIS learning, aiding more accurate and personalized training; (ii) to provide intelligent solutions for training assistance validated in a comprehensive way; and (iii) to increase the realism and quality of virtual training environments and, consequently, improve the quality of surgical training.

5. Conclusions

The application of AI in MIS surgical training remains a developing field of research, which presents great potential for exploring future applications and synergies between

the fields of technical and clinical research. Thus, the present scoping review found some limitations in some studies on the application of AI in MIS surgical training, due to small numbers of surgeons, lack of external validation, small datasets, and lack of clinical oversight by expert surgeons and expert data analysts. Some advances have also been completed, or are in the process of being successfully completed, such as automation of gesture and surgical action recognition, improved feedback to surgeons, or self-tuning and customization of the learning curve for surgeons. To this end, the application of innovative AI techniques could complete these tasks. In addition, AI has the potential to give rise to a new class of medical devices specifically for surgical training to improve safety and learning efficiency. Finally, future challenges such as automating optimal trajectories and steps during the training process and increasing realism in simulations need to be solved in the coming years.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/surgeries6010007/s1. Table S1: Preferred Reporting Items for Systematic reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR) Checklist.

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