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The Role of Artificial Intelligence in Predicting Flap Outcomes in Plastic Surgery: Protocol of a Systematic Review

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Introduction: Free flap surgery encompasses reconstruction of diverse tissue defects. Flap failure and complications such as infection and ischemia remain a concern following flap surgery, with the current post-operative standard of care being frequent bedside monitoring. Artificial intelligence such as machine learning models could help support surgeons in postoperative monitoring and predicting complications. The purpose of this systematic review is to provide the framework for a review analyzing the existing literature behind the use of artificial intelligence in assessing flap surgery outcomes and predicting postoperative complications.
Methods: A systematic review will be conducted using EMBASE and MEDLINE (1974 to October 2021) to identify relevant literature. This will include studies investigating Artificial Intelligence and machine learning models used in the postoperative setting of flap surgery. Primary outcomes will include evaluating the accuracy of evaluating outcomes following flap surgery based on these models, including: flap success, healing and complications up to 1 month following surgery. Secondary outcomes include the analysis of benefits and drawbacks of using machine learning models for outcomes following flap surgery. Studies will be screened by two independent reviewers; risk of bias will be assessed using the Cochrane risk of bias tool with methodological quality assessed using the QUADAS-2 tool.
Discussion: This protocol will provide the framework for a review summarizing the current literature exploring the role of Artificial Intelligence for flap surgery outcomes. Results will help provide surgeons with an overview of current applications and identify areas of potential further research and development.
Conclusion: As current clinical practice is regular bedside monitoring, integrating Artificial Intelligence could make the process more efficient, accurate and safer for patients and reduce labour burden or healthcare system costs. This review can help identify areas of potential and improvement which could further aid achieving successful outcomes following flap surgery.

Keywords: artificial intelligence; machine learning; flap surgery; outcomes; complications; postoperative; monitoring; flap success

Introduction

Flap Surgery

Free flap surgery has grown to encompass reconstruction of diverse tissue defects, ranging from soft tissue to bone to mucosal tissue [1]. Free flaps provide immediate reconstructive options in oncologic settings such as breast cancer post-mastectomy reconstruction [2], head and neck cancer surgery [3], trauma settings, osteomyelitis [4] and lower extremity reconstruction [5]. Although the scope of flap surgery has expanded, the goals remain the same: to reconstruct the anatomy and restore function, and to improve the patient's quality of life [1]. Despite advances in free flap surgery over the years, flap failure and infection are not uncommon post-operative outcomes [5,6]. Free flap failure due to vascular compromise has been found to range from 2-5% in various studies [7-10]. Other studies have found regular monitoring increases flap salvage rates to between 30 and 70% [10-13]. Complications during the postoperative course can lead to poor outcomes and negative impacts on the patient quality of life [5].

A major concern following flap surgery is the possibility of an occlusive event at the vascular pedicle of the free flap, for example, due to arterial or venous thrombosis [14]. The length of time for which a flap experiences occluded blood flow can severely impact survival of the flap, suggesting a need for effective monitoring in case early intervention is required [14]. Other potential complications include infection, hematoma and bleeding [15]. The current approach to postoperative flap monitoring is limited to frequent clinical bedside monitoring, with new techniques being investigated regularly [10]. Clinical assessment involves subjective evaluation from the healthcare provider: examining flap colour, appearance, capillary refill time, temperature, bleeding time as well as acoustic Doppler use for blood flow detection. The current standard of care is clinical flap monitoring, typically done every 2-4 hours for the first 2-3 days following the operation, and often requires patients to be admitted to an intensive care unit or step-down ward for nursing availability. Novel, objective methods of flap evaluation can reduce the need for frequent and labour-intensive clinical evaluation and provide a standard approach to monitoring. However, given that clinical assessment is very effective, any new method would have to significantly improve patient outcomes [10].

Artificial Intelligence in Medicine

Artificial Intelligence (AI) has recently emerged as an innovative tool which healthcare workers have been quick to adopt. The uses range from improving diagnosis of several medical conditions, to predicting post-treatment and postoperative outcomes. AI functions by collecting and analyzing large amounts of patient data and utilizing models which can detect patterns in this data to make decisions. A main subtype of AI is machine learning (ML) where algorithms examine associations and patterns in large data sets - this includes supervised and unsupervised learning [16]. Supervised learning models use algorithms created for predicting a specific outcome with training data, whereas unsupervised learning models look for novel patterns in a set of data with no training [16]. Another subtype of AI is deep learning which involves machine learning models using neural networks and continuous training to improve accuracy of predictions [16]. AI in medicine has been adopted in many settings, and largely aims to support the role of the physicians [17] and shows promise for many advances in plastic surgery [23] including predicting healing post-burn surgery [24], monitoring post-microsurgery [25], predicting outcome of peripheral nerve graft surgery [26] as well as aesthetic surgery following breast cancer [27].

Artificial Intelligence and Flap Surgery

AI holds potential for bridging the gap that exists in postoperative management of flap surgery patients. As these patients require frequent, labour-intensive monitoring for the first few days following surgery, there have been many studies investigating the role of AI in predicting outcomes as well as monitoring outcomes postoperatively. In microvascular breast reconstruction, ML models have been used to predict flap failure based on patient characteristics and comorbidities with high sensitivity and specificity [28]. Additionally, a Smartphone application has been shown to accurately monitor postoperative microsurgery outcomes providing an inexpensive option which holds potential for flap surgery settings [25]. Currently no systematic review has summarized these findings. As such, the purpose of this review is to analyse the existing literature investigating the use of AI such as ML in assessing flap surgery outcomes and predicting complications postoperatively.

Methods

We will perform a systematic review in accordance with PRISMA guidelines. This review has been registered on Open Science Framework (osf.io/2mscq).

Search Strategies

We will perform a search using the MEDLINE and EMBASE databases. A combination of free text and Medical subject headings (MeSH) terms will be used in this search (Table 1, Table 2 & Table 3).

Table 1. Categories and keywords used to formulate search strategy.

Categories	**Keywords**
Artificial Intelligence	machine learning • supervised machine learning/ or unsupervised machine learning neural networks (computer) algorithms • radiomics • learning algorithm • coding algorithm • computer heuristics computer language or prediction or simulation or aided diagnosis
Surgery	flap surgery reconstructive surgery plastic surgery surgery
Patient outcomes	recovery infection mortality or morbidity

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Categories	Keywords
	healing complications success digital or images

Table 2. Search strategy for EMBASE (OvidSP Interface), 1974 to 15 Oct 2021.

#	Search	Results
1	exp machine learning/	274639
2	"neural networks (computer)".mp.	206
3	supervised machine learning/ or unsupervised machine learning/	3316
4	(radiomics or learning algorithm or coding algorithm or computer heuristics).ti,ab,kw.	13803
5	(comput* language or comput* prediction or comput* simulation or comput* aided diagnosis).ti,ab,kw.	24413
6	exp algorithms/	456450
7	1 or 2 or 3 or 4 or 5 or 6	627241
8	(surgery? adj3 (flap? or plastic? or reconstruct* or outcome*)).ti,ab,kw.	87380
9	exp flap surgery/ or reconstructive surgery/ or plastic surgery/ or surgery/	686596
10	(flap? adj3 (outcome* or complications or success or digital or images or mortality or morbidity or healing)).ti,ab,kw.	5547
11	8 or 9 or 10	742948
12	7 and 11	9392
13	Animal/ not (human/ and animal/)	1123815
14	12 not 13	9360
15	Limit 14 to article	2074

Table 3. Search strategy for MEDLINE, 1946 to Sept 2021.

#	Search	Results
1	exp machine learning/	36434
2	"neural networks (computer)".mp.	34745
3	supervised machine learning/ or unsupervised machine learning/	1621
4	(radiomics or learning algorithm or coding algorithm or computer heuristics).ti,ab,kw.	10383
5	(comput* language or comput* prediction or comput* simulation or comput* aided diagnosis).ti,ab,kw.	20768

6	exp algorithms/	372403
7	1 or 2 or 3 or 4 or 5 or 6	395785
8	(surgery? adj3 (flap? or plastic? or reconstruct* or outcome*)).ti,ab,kw.	65202
9	exp flap surgery/ or reconstructive surgery/ or plastic surgery/ or surgery/	118599
10	(flap? adj3 (outcome* or complications or success or digital or images or mortality or morbidity or healing)).ti,ab,kw.	4776
11	8 or 9 or 10	171841
12	7 and 11	1768
13	Animal/ not (human/ and animal/)	4889858
14	12 not 13	1751
15	Limit 14 to journal article	1665

Selection of Studies

Following searches in the databases, these studies will be screened by two independent reviewers in duplicate using predetermined criteria. First, title and abstracts will be screened for eligibility, followed by full text review for inclusion. Conflicts in the title and abstract screening will advance to full text screening for eligibility. Discrepancies in full text screening will be resolved by discussion with a third reviewer for inclusion.

Eligibility Criteria

Participants: Studies including adult patients (18 years or older) undergoing flap surgery will be included. Animal studies will be excluded. Studies from inception of database to 2021 will be included.

Intervention

The studies included will use machine learning models with deep learning or neural networks as an intervention with the aim to identify prognosis following flap surgery as compared to clinical monitoring alone. Articles will be excluded if clinical data was not used. Various machine learning models will be used.

Outcomes

Primary outcomes will be evaluating the machine learning models investigated by the study. This includes the accuracy of evaluating outcomes following flap surgery based on these models, including, for example, healing and incidence of complications up to 1 month following surgery. Another primary outcome will be to examine the effectiveness of the ML models in predicting outcomes of flap surgery before these occur; these might vary depending on the study, as measured by likelihood or odds ratio. If studies have not included these likelihood or odds ratios, we will also include studies that allow extraction of the data and will be calculated

Secondary outcomes will include the analysis of benefits and drawbacks of using machine learning models for outcomes following flap surgery rather than classical clinical expertise.

Studies

Primary observation studies which assess the effectiveness of machine learning models in assessment or prediction of outcomes following flap surgery, compared to current clinical standards will be included. There will be no geographical restriction on studies. Exclusion criteria include case reports, studies not using clinical data, non-English language articles and other review articles.

Data Extraction, Collection and Analysis

Following study selection, two reviewers will extract data independently and in duplicate from the studies using a standardized form. The data collected will include:

- Study characteristics: authors, title, year of publication, study design, country
- Participant characteristics: number of participants, age, sex, location
- Use of model: characteristics of the model, details of application i.e. outcomes
- Outcomes of study: specificity, sensitivity, accuracy, predictive value for outcomes, post-operative success, complications
- Any adverse events reported, or weaknesses identified.

Risk of Bias

Risk of bias in the studies will be assessed using the Cochrane Risk of Bias assessment tool. The methodological quality of the full-text articles will be independently evaluated by two reviewers using the QUADAS-2 tool [29]. This tool will be used to determine the ROB within four domains: patient selection, index test, reference standard, and flow and timing. Based on the information provided in the included studies, the ROB will be rated low, intermediate, or high for these domains separately.

Data Analysis

Two reviewers will independently assess heterogeneity between studies including the machine learning model used, the outcomes (i.e. flap success, complications, infection etc), the purpose of the model (i.e. diagnosis, monitoring or treatment), and the population. Demographics and study characteristics will be presented as proportions and means. If sufficient homogenous studies in terms of intervention and outcomes are identified, a meta-analysis (quantitative analysis) will be performed. These analyses will vary depending on the outcome:

- Rates of infection based on proportions
- Flap success based on binary yes or no
- Any other complication based on counts or proportions

Heterogeneity of studies will be calculated using I^2 statistic [30]. For the heterogeneous cohorts (I^2>50), a random-effects model will be used. Sensitivity analyses will depend on the studies, and these may be repeated as required. Finally, the quality of the evidence will be assessed using The Grading of Recommendations Assessment, Development and Evaluation (GRADE) approach [31].

Results

To date, we have run searches on EMBASE and MEDLINE based on our search strategy (Table 1, Table 2 & Table 3). These studies will be screened and assessed for inclusion over the coming months. We anticipate that studies will include various models and outcomes, and hope to find areas of potential regarding the role of AI in flap surgery.

Discussion

The selected studies will help identify current use and limitations of Artificial Intelligence in predicting and monitoring outcomes post flap surgery, as well as areas for further improvement. Extracted data will be analyzed for the performance of the AI models compared to current clinical practice, and potential in the field. We hope to be able to identify current AI models that might be used for monitoring patients or predicting outcomes and improving patient outcomes following flap surgery. The aim of this review is to systematically identify such models, in order to help familiarize plastic surgeons interested in flap surgery with the potential of AI in this field. To the author's knowledge, this is the first systematic review to evaluate the role of AI in flap surgery.

Conclusions

This systematic review protocol aims to provide the framework for a review of the current literature examining the role of AI in flap surgery postoperative outcomes. As current practice is regular bedside monitoring, systems that could make the process more efficient or safer for patients could reduce healthcare worker burden as well as healthcare costs. This review can help identify areas of potential and improvement which could further aid achieving successful outcomes following flap surgery.

List of Abbreviations Used

AI: artificial intelligence
ML: machine learning

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Ethics Approval and/or Participant Consent

Not applicable as this is a systematic review protocol.

Authors' Contributions

SM: made contributions to the design of the study and planning, collected and analysed data, drafted the manuscript, and gave final approval of the version to be published.
RD: contributed to study design and planning, assisted with the collection and analysis of data, drafted the manuscript and gave final approval of the version to be published.
IC: made contributions to the design of the study, the interpretation and analysis of the data, revised the manuscript critically, and gave final approval of the version to be published.

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