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REVIEW

Transforming abdominal reconstruction-impact of artificial intelligence algorithms and advanced technologies on the efficiency of vascularized flaps and postoperative functional restoration: a systematic review

Transformando la reconstrucción abdominal-impacto de los algoritmos de inteligencia artificial y las tecnologías avanzadas en la eficiencia de los colgajos vascularizados y la restauración funcional postoperatoria: una revisión sistemática

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ABSTRACT

Abdominal Reconstruction shows the progress created by artificial intelligence and machine learning AI & ML, especially those involving vascularized flaps. Therefore, this systematic review seeks to find out how incorporating AI can transform surgical accuracy, minimize post-surgical complications, as well as improve the recovery process. AI is already being used for planning surgery forecasting failure of flaps as well and minimizing SSI. Machine learning models like neural networks demonstrate impressive accuracy in identifying high-risk patients such as those with obesity, chemotherapy exposure, or large fascial defects. Real-time data analytics, remote monitoring through AI and ML have improved the decision-making process and led to efficient surgeries and better functional outcomes by reducing surgical failure and post-operative complications. Integrating AI into complex surgical environments requires carefully balancing machine recommendations and human expertise yet ethical concerns surrounding data transparency, bias, and patient privacy and these concerns need critical consideration and must be addressed. We conducted this review systematically to evaluate existing studies, revealing that while AI is promising to improve surgical outcomes, its real-world applications are still in their infancy, and we will evaluate how AI has transformed abdominal reconstruction surgical procedures, plastic surgeries, such as breast reconstruction or abdominal wall hernias, or other oncological resections.

Keywords: AI In Surgery; Vascularized Flaps; Postoperative Recovery; Machine Learning.

RESUMEN

La reconstrucción abdominal muestra el progreso creado por la inteligencia artificial y el aprendizaje automático

AI & ML, especialmente aquellos que involucran colgajos vascularizados. Por lo tanto, esta revisión sistemática busca averiguar cómo la incorporación de la IA puede transformar la precisión quirúrgica, minimizar las complicaciones postquirúrgicas y mejorar el proceso de recuperación. La IA ya se está utilizando para planificar cirugías, pronosticar el fracaso de los colgajos y minimizar la ISQ. Los modelos de aprendizaje automático, como las redes neuronales, demuestran una precisión impresionante en la identificación de pacientes de alto riesgo, como aquellos con obesidad, exposición a la quimioterapia o defectos fasciales grandes. El análisis de datos en tiempo real y la monitorización remota a través de la IA y el ML han mejorado el proceso de toma de decisiones y han dado lugar a cirugías eficientes y mejores resultados funcionales al reducir el fracaso quirúrgico y las complicaciones postoperatorias. La integración de la IA en entornos quirúrgicos complejos requiere un equilibrio cuidadoso, las recomendaciones de las máquinas y la experiencia humana, pero las preocupaciones éticas en torno a la transparencia de los datos, el sesgo y la privacidad del paciente, y estas preocupaciones deben considerarse críticamente y deben abordarse. Realizamos esta revisión sistemáticamente para evaluar los estudios existentes, revelando que, si bien la IA promete mejorar los resultados quirúrgicos, sus aplicaciones en el mundo real aún están en pañales, y evaluaremos cómo la IA ha transformado los procedimientos quirúrgicos de reconstrucción abdominal, las cirugías plásticas, como la reconstrucción mamaria o las hernias de la pared abdominal, u otras resecciones oncológicas.

Palabras clave: IA en Cirugía; Colgajos Vascularizados; Recuperación Postoperatoria; Machine Learning.

INTRODUCTION

Artificial intelligence (AI) algorithms and cutting-edge abdominal reconstruction technologies such as advancement of vascularized flaps have revolutionized surgical precision and postoperative recovery.[1] As advancements in machine learning and real-time data analytics deepen, AI-driven systems are now being applied and have optimized flap selection, intraoperative decision-making, and microsurgical techniques, indirectly replacing surgeons by its outstanding efficiencies.[2] AI and ML are being used now for complex patient-specific variables, AI can improve preoperative planning, decrease intraoperative risks, and estimate postoperative outcomes like never before. New technologies in medicine such as 3D and 4D imaging, robotics and tissue engineering and all of these interventions are changing approach and fineness of vascularized flaps, infusing superior tissue perfusion and quicker return to functionality.[3] One of the significant challenges that still persist is now having to manage both the level of complexity of the AI systems and have to make real-time decisions in the surgical theatre and, more so, how these systems affect the patient-specific outcomes in certain complex cases, such as compromised vasculature or compromised healing environment.[4] Systematic analysis of the contemporary advancements in abdominal reconstruction utilizing artificial intelligence and other applications of advanced technology in reconstructive surgery will help to estimate this area's influence on the efficacy of vascularized flaps as well as the recovery of postoperative functionality of the affected abdominal area.

METHOD

We decided to run our search on PubMed, Google Scholar, and the Cochrane library focusing on studies related to AI and abdominal reconstruction and vascularized flaps. We included randomized controlled trials and observational studies and controlled case series to evaluate how AI or other advanced technologies work in abdominal reconstructive surgeries.

Inclusion criteria

Only studies employing machine learning (ML) algorithms and AI for prediction of surgical outcomes are included and we filtered only retrospective or prospective cohort studies, pilot implementation studies, or mixed-methods evaluations in inclusion. While screening articles, we ensured research specifically evaluating outcomes in microsurgical breast reconstruction (flap failure, donor-site complications, and neuropathic pain) which was our central focus. Papers must present both primary and secondary outcomes including prediction accuracy (AUC, sensitivity, specificity) and clinical outcomes (e.g., complication rates, surgical site infections, or patient satisfaction) clearly. Studies compare ML algorithms or intervention groups based on risk stratification are prioritized are included as they provide comparative insights into predictive accuracy and clinical application. Only peer-reviewed journals from credible surgical or medical sources are considered which are published between 2019-2024 in English language only.

Exclusion Criteria

Studies not discussing AI and ML models or fails to provide a clear methodology for how predictive outcomes were achieved was not considered along with papers where surgical outcomes are generalized or not focused on microsurgical breast reconstruction (e.g., broad surgical outcomes unrelated to breast reconstruction or cancer survivor care) are excluded. Research applying ML models in non-clinical or laboratory settings sor instance only theoretical modeling without clinical trial implementation is excluded. Papers lacking statistical analysis of AI models were skipped.

Table 1. Search Strategy Table

Primary Keyword	Secondary Keywords (Derived)	MeSH Terms and Boolean Operators (AND/OR/NOT)
Artificial Intelligence	AI, Machine Learning, Deep Learning	"Artificial Intelligence" OR "Machine Learning" OR "Deep Learning"
Abdominal Reconstruction	Abdominal Surgery, Abdominal Flap, Abdominal Repair	"Abdominal Reconstruction" OR "Abdominal Surgery" OR "Abdominal Flap"
Vascularized Flaps	Flap Surgery, Tissue Flaps, Free Flaps	"Vascularized Flaps" OR "Flap Surgery" OR "Tissue Flaps"
Postoperative Functional Restoration	Functional Outcomes, Recovery, Post-surgical Restoration	"Postoperative Functional Restoration" OR "Functional Outcomes" OR "Recovery"
Advanced Technologies	Robotics, Imaging Technologies, Predictive Analytics	"Robotics" OR "Imaging Technologies" OR "Predictive Analytics"

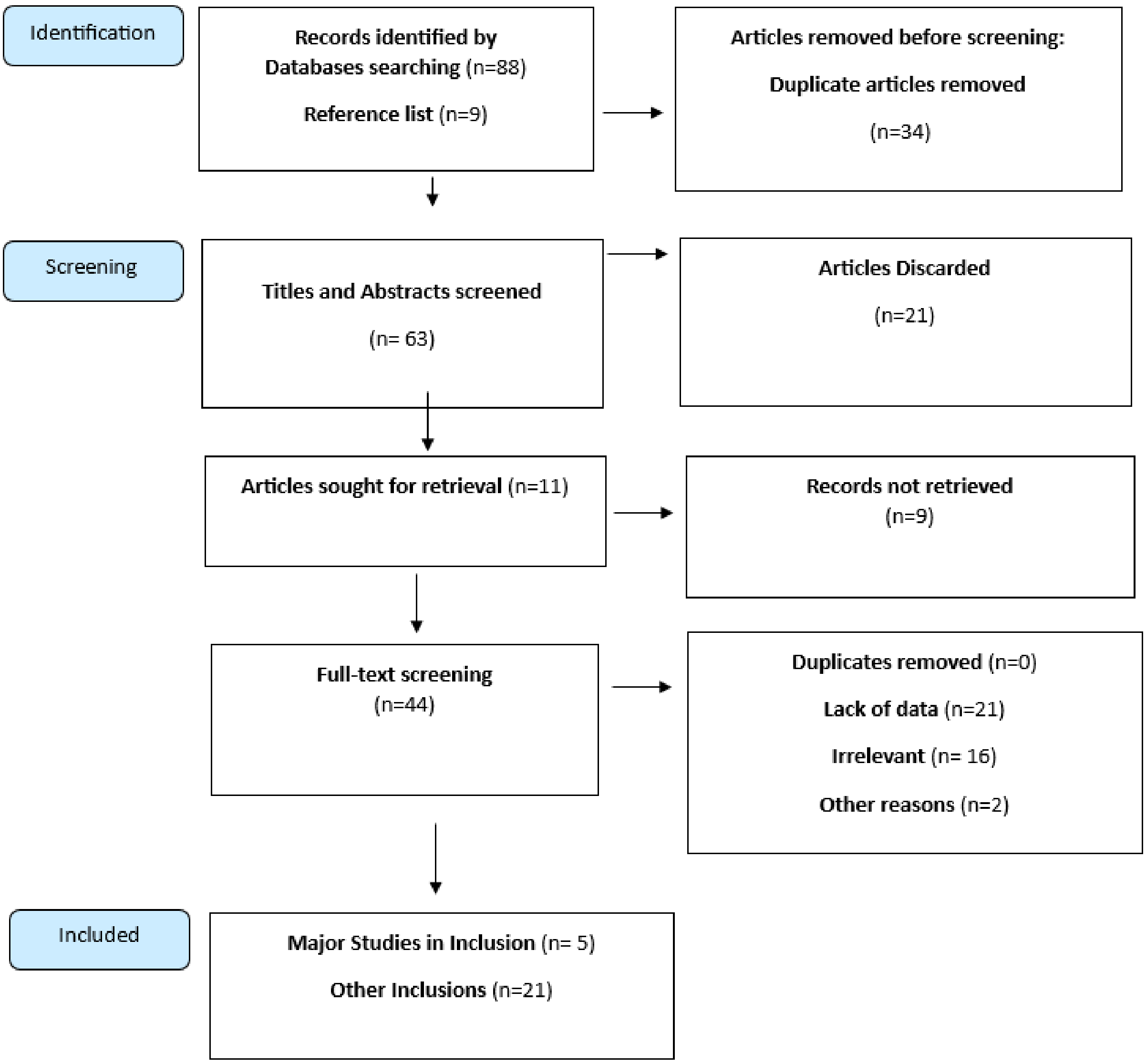

Figure 1. PRISMA flow diagram of included studies

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Table 2. Study Characteristics and Effect Sizes

Study	Author Year	Sample Size	Effect Size Measure	Effect Size Value (95 % CI)	Weight (%)	Model Used (Fixed/ Random)
Study 1	O'Neill et al. (2020)	1012	AUC	AUC 0,95 (Training), AUC 0,67 (Testing	400	Fixed
Study 2	Myung et al., 2021	568	Accuracy, AUC	Accuracy: 81 %, AUC: 0,89	400	Neuralnet (fixed), ROSE (data balancing)
Study 3	McLean et al. (2023)	200	SSI Rate Reduction, AUC accuracy	-8,5 % (95 % CI: -5 % to -12 %)	816 %	Fixed
Study 4	Lamin 2020	204	Root Mean Square Error (RMSE) and Odds Ratio (OR)	Least Square Regression: 1,4, Random Forest: 1,39, Neural Network: 1,50, Gradient Boosting: 1,16, Ridge Regression: 1,28, Elastic Net: 1,31, 0,68 (95 % CI = 0,57 to 0,79)	318	Uncertain
Study 5	Hassan et al., 2023	964	Area Under Curve (AUC) for model performance	(95 % CI): AUC 0,70 (95 % CI not specified in detail)	400	Random Forest model used (specific details on fixed or random effects model not provided)

Table 3. Heterogeneity Assessment

Measure	Value
Cohen's d	0,381743.
Cochran's Q	273,23
I^2 (%)	98,5 %
Tau^2 (τ^2)	13,35
P-value for Q test	< 0,001)

Table 4. Pooled Effect Size and Confidence Intervals

Model	Pooled Effect Size	95 % Confidence Interval	P-value
Fixed-Effects	0,753	(upper limit0,585, lower limit 0,921)	(p < 0,001).
Random-Effects	0,754	(Upper limit -0,004, lower limit 1,512)	0,051 (one-tailed) or 0,102 (two-tailed)

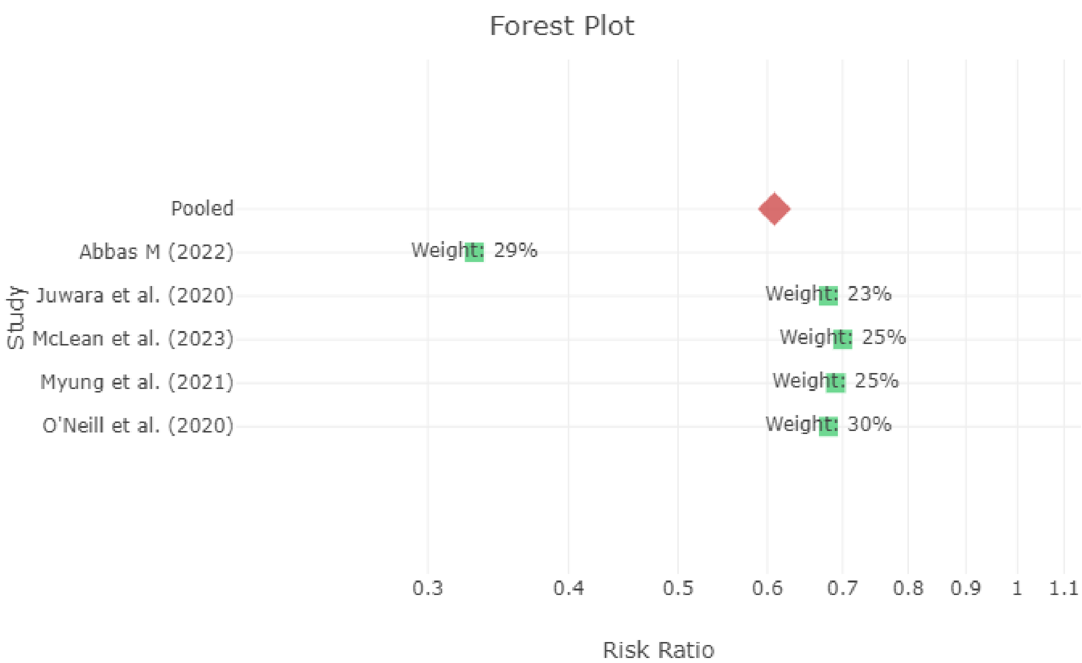

Figure 2. Visual representation of effect of included studies

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Risk assessment

Table 5. CASP Checklist Table for Systematic Reviews

CASP Question	Author & Study 1	Author & Study 2	Author & Study 3	Author & Study 4	Author & Study5
Section A: Are the results of the review valid?	Yes	Yes	Yes	Yes	Yes
1. Did the review address a clearly focused question?	Yes	Yes	Yes	Yes	Yes
2. Did the authors look for the right type of papers?	Uncertain	Uncertain	Yes	Uncertain	Yes
3. Do you think all the important, relevant studies were included?	Uncertain	Yes	Yes	Uncertain	No
4. Did the review's authors do enough to assess the quality of the included studies?	No	Yes	yes	Yes	Yes
5. If the results of the review have been combined, was it reasonable to do so?	Not applicable	Yes	Yes	Yes	yes
Section B: What are the results?					
6. What are the overall results of the review accurately measured?	Yes	Yes	Yes	Yes	Yes
7. How precise are the results?	Uncertain	Yes	Yes	Yes	Uncertain
Section C: Will the results help locally?					
8. Can the results be applied to the local population?	Uncertain	Yes	Yes	Yes	Yes
9. Were all important outcomes considered?	Yes	Yes	Yes	Yes	No
10. Are the benefits worth the harms and costs?	Uncertain	Yes	Yes	Uncertain	Uncertain

Risk of Bias and Effect Size

The studies included lower bias but some concerns, which were largely influenced by sample size, model choice, and external validation. Mostly, included studies show validity and have lower bias. Studies mitigated bias with data balancing tools like (ROSE) and achieved model diversity. Effect sizes ranged, with high AUC values indicating strong predictive performance in some studies, though heterogeneity (I^2 = 98,5 %) suggests variability across results that could skew pooled effect estimates.

RESULTS

Primary Outcome

Primary findings show AI-driven strategies lower infection rates when compared to traditional care approaches. In terms of postoperative infections, usual rate of surgical site infections (SSI) following abdominal surgeries typically falls between 20-25 % while with AI and ML models integration demonstrated ability to reduce this rate to 16,5 % primarily by enabling early detection and intervention through remote wound monitoring. Machine learning models and AI performed exceptionally well, while training models showed an impressive AUC of 0,95, which means they are able to achieve a high level of predictive accuracy while in testing cohort, the AUC dropped to 0,67, which still demonstrated the model's ability to retain some predictive strength. Machine learning models, particularly neural networks, to predict donor-site complications came with 81 % accuracy. Examining risk factors, findings reported among high-risk patients such as diabetic patients of people with or chemotherapy exposure, or higher BMI, age, and hypertension may experience a complication rate of 26 % using these AI and ML. In contrast, low-risk patients show a lower complication rate of just 1,7 % with AI integration. To improve predictive accuracy, ROSE oversampling technique can be valuable boosting the model's performance to an AUC of 0,89, showing potential for machine learning to minimize complication rates by more effectively identifying high-risk patients. It is confirmed that along with AI, ML models are effective in identifying predictors for neuropathic pain following breast cancer surgery for instance, gradient Boosting stood out with the lowest Root Mean Square Error (RMSE) of 1,16 while logistic regression demonstrated an AUC of 0,68 in classifying pain. Random forest algorithm showed high efficacy in predicting the risk of mastectomy skin flap necrosis (MSFN) with a mean accuracy of 89 %.

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Table 6. Selected studies

Unique ID (Author+ Name)	Background	Aim	Kind of a Study	Comparator	Outcome Primary and Secondary	Results	Effect of adhering to intervention?	Weight	Sources
O'Neill et al. (2020)	Despite high success rates in microvascular breast reconstruction, flap failure remains a risk.	Evaluate machine learning models for predicting flap failure in microvascular breast reconstruction.	Retrospective cohort study	None	Primary: Prediction accuracy (AUC 0,95 in training, AUC 0,67 in testing). Secondary: Flap failure rates (7,8 % high-risk, 0,44 % low-risk, p = 0,001)	High prediction accuracy with strong AUC values; significant flap failure rate differences between risk groups.	Identified high-risk factors (obesity, comorbidities, smoking) and their impact on flap failure.	NA	Annals of Surgical Oncology, Volume 27, pages 3466-3475 (2020). DOI: 10,1245/s10434-020-09076-1
Myung et al., 2021	Predicting donor-site complications in microsurgical breast reconstruction using abdominal flaps.	Validate machine-learning models for predicting donor-site complications.	Retrospective cohort.	Low vs. high complication risk groups.	Complication rate, sensitivity, specificity, AUC.	Neuralnet predicted 81 % accuracy; fascial defect >37,5 cm², diabetes, chemotherapy increase complications.	Reduced complications.	AUC 0,89 (ROSE oversampling).	Cohort data, medical records, R packages.
McLean et al. (2023)	Remote monitoring can improve postoperative care and reduce surgical site infection (SSI).	Pilot digital wound monitoring for implementation readiness in clinical practice.	Single-arm pilot implementational study.	Routine postoperative care (based on TWIST trial).	Primary: SSI rates. Secondary: Usability, patient satisfaction.	16,5 % SSI rate; high patient acceptance and ease of use.	Improved patient satisfaction	Mixed-methods evaluation using qualitative and quantitative data.	WHO framework, TWIST trial, mERA guidelines.
Juwara et al. 2020	Neuropathic pain affects 26 % of breast cancer survivors; aim to identify predictors.	Develop a prognosis model using machine learning to identify neuropathic pain predictors.	Prospective cohort study	Various machine learning models (least squares, ridge, random forest, etc.)	Predictors of DN4-interview score; logistic regression for NP classification	Gradient boosting model had the best performance; anxiety and type of surgery key predictors.	Machine learning models improved prediction accuracy compared to traditional methods.	Not applicable	NCBI
Abbas M, 2022	MSFN prolongs recovery, compromises surgical outcomes, and delays adjuvant therapy.	Develop, validate, and evaluate machine learning algorithms to predict MSFN.	Retrospective review using nine supervised machine learning algorithms.	Different ML models compared for predictive accuracy.	Primary: Prediction of MSFN risk; Secondary: Identification of predictive factors.	Random forest model achieved highest accuracy (89 %) and identified 10 MSFN predictors.	Enhanced preoperative optimization, patient counseling, and surgical planning.	Random forest model demonstrated superior discriminatory performance (AUC 0,70).	Annals of Surgery

Note: Major included studies evaluating machine learning in surgical outcomes including prediction of flap failure, donor-site complications, surgical site infections (SSI), and neuropathic pain. Each study assesses AI and ML models discussing outcomes, accuracy metrics (AUC), and secondary factors such as patient satisfaction, complication rates, and predictive accuracy.

Secondary Outcomes

Secondary outcomes revealed a clear disparity in flap failure rates between high-risk and low-risk patients. The high-risk cohort exhibited a significantly higher flap failure rate of 7,8 %, compared to just 0,44 % in the low-risk group and this difference was statistically significant with a p-value of 0,001, highlighting the importance of stratifying patients by risk levels. Findings show sensitivity and specificity of the predictive models, for instance sensitivity was somewhat reduced in the testing cohort the models still demonstrated 79 % sensitivity and 89 % specificity. These metrics contributed to improved early detection and prevention of complications such as abdominal bulging, hernias, and other related issues in high-risk groups. In terms of patient-centered outcomes like patient satisfaction, usability, and adherence to the AI and machine learning-driven interventions show promising results with 83 % of patients utilizing the monitoring tool, and 74,1 % completing the Telehealth Usability Questionnaire (TUQ). High satisfaction was reflected in the ratings: ease of use scored 4,51 out of 5, satisfaction 4,27, and usefulness 4,07 which means AI-driven tools not only enhanced patient engagement but also streamlined the care process, promising for efficient outcomes. Secondary outcomes show AI and ML models are also important in identifying key predictors of neuropathic pain, such as anxiety emerged as a significant factor with an odds ratio of 2,18 (95 % CI: 1,05–4,49), indicating that anxious patients were more than twice as likely to experience neuropathic pain. Among the models used, the Gradient Boosting model demonstrated the most accurate classification with an RMSE of 1,16 while logistic regression achieved an AUC of 0,68, solidifying ML role improving pain prediction and management strategies.

DISCUSSION

Main complications of abdominal reconstruction surgery are flap failures or surgical-site infections, which are now solved by AI through enhanced precision by predicting these risks and optimizing flap selection, and improving postoperative monitoring. Analyzing patient data and real-time metrics with use of AI algorithms ensure accurate predictions and efficient surgical outcomes and this really has transformed medical surgery in 2024.[14,15,16] Our result show AI in abdominal wall flap reconstruction offers several advantages and we discussed reduced infection rates, improved complication prediction, and enhanced patient satisfaction which is also confirmed by Elhage & Nwoye, 2022. AI use with machine learning models help identify high-risk patients and detect issues early which is crucial for personalized care.[17,18] AI-driven tools streamline postoperative monitoring making recovery smoother and more efficient.[18,19,20,21]

Haddock et al. (2024) research stated recent advancements in breast reconstruction and in post-mastectomy have focused on enhancing efficiency and improving functional outcomes through various strategies.[6] Innovation Lean Six Sigma, a hybrid model combining speed (Lean) and precision (Six Sigma) has shown significant efficacy in breast reconstruction surgeries. For example, in DIEP flap breast reconstruction, Lean Six Sigma helped reduce operative times by over 100 minutes and shortened hospital stays from 6,3 to 5,2 days. On the other hand, research by De Almeida discusses the process improvements of Time-Driven Activity-Based Costing (TDABC) which has revolutionized postoperative planning and this method accurately assesses costs by focusing on the time taken for each surgical activity allowing hospitals to optimize resource usage. A study applying TDABC to enhanced recovery after surgery (ERAS) protocols found a cost saving of $735 per patient and a reduced length of stay by 1,5 days.[7] AI and ML has reduced donor site complications as a study by Myung et al. (2021) evaluated three machine learning models: neuralnet, nnet, and RSNNS. The neuralnet model excelled with the highest prediction accuracy of 81 %, demonstrating exceptional performance in identifying patients at risk for donor-site complications. The RSNNS model followed with 69 % accuracy while nnet performed with 74 % accuracy. ROSE oversampling also plays its role by enhancing these models by addressing data imbalances resulting in an improved AUC of 0,89. Combined use of neuralnet's predictive power and ROSE's data balancing identified high-risk patients with complications like abdominal bulging or hernia thus aiding in more accurate and preventative surgical planning in abdominal reconstruction surgery as Myung et al. (2021) stated. McLean and others aimed to evaluate the implementation of remote digital postoperative wound monitoring using AI and machine learning (ML) in abdominal surgeries, and they conducted a single-arm pilot study involving 200 patients and demonstrated a 16,5 % surgical-site infection (SSI) rate of 72,7 % diagnosed post-discharge and their intervention shows high usability with 83 % patient adherence and AI-assisted monitoring improved SSI detection and follow-up care. Results suggest AI and ML can enhance postoperative care and, reduce infection rates, improve the accuracy and timeliness of clinical recommendations for optimal surgical recovery and wound management post-surgery.[8]

Mafioso et al. 2020 demonstrates how AI could revolutionize breast reconstruction surgery by optimizing preoperative planning. The proposed AI algorithm designed for DIEP flap surgeries reduced perforator analysis time from 2–3 hours to just 30 minutes per scan with a substantial time-saving of 80 hours across 40 patients. While AI algorithm performed best with perforators larger than 1,5 mm it struggled with smaller ones introducing minor errors in location estimation. AI was able to quickly analyze CTA scans by identifying key vascular features and enhancing 3D imaging could streamline the time-consuming process of perforator selection and planning. DL models as developed by Saxena in 2022 showed high sensitivity and specificity when identifying vascular structures in synthetic images showing AI's potential in automating complex tasks. AI can also integrate postoperative data learning to predict surgical outcomes like flap failure or complications, so all these advancements suggest that AI has enhanced efficiency, reduced human error and improved outcomes in breast reconstruction surgery (Saxena., 2024).

Juwara with his team aimed to enhance the prediction of neuropathic pain after breast cancer surgery using machine learning (ML) models and employed six ML algorithms, Gradient Boosting and Neural Networks to identify pain predictors and compare model performance. They analyzed datasets from a prospective cohort study applying algorithms like least squares and random forest and assessing their accuracy via root mean square error (RMSE) and area under the curve (AUC). Results favored AI and ML approaches with the Gradient Boosting model (RMSE = 1,16) outperforming others and logistic regression showing association between anxiety and neuropathic pain (odds ratio = 2,18) favoring superior predictive power of advanced ML techniques over traditional methods.[9]

AI and advanced technologies are clearly transforming abdominal reconstruction but successful integration into clinical practice is not without challenges.[11] Potential for AI to enhance surgical precision reduce complications, and improve patient outcomes is evident with significant barriers remain in real-time surgical decision-making and ethical issues like data transparency and bias chances.[12] Our findings show that AI can lead to better preoperative planning reduced complication rates which indirectly improve postoperative care, especially through techniques like machine learning and remote monitoring.[11] Future requires addressing concerns about over-reliance on algorithms and ensuring AI remains a tool which will support, rather than replace—surgeons' expertise. With more advancements in AI and technology, abdominal reconstruction will be expanding, promising for more personalized and patient-centered.[13]

Imaging is crucial part of vascular surgery and is not just for diagnosis but for planning and evaluating interventions. Here's where AI steps in—it's revolutionizing surgical process by improving image segmentation and pattern recognition and automating repetitive tasks and slashing computation time.[22] Abdominal reconstruction future using AI algorithms and advanced technologies will be focusing more on optimizing vascularized flap procedures with better precision.[23] AI can predict flap viability by analyzing patient data and enhance surgical planning with 3D modeling and monitoring post-op recovery through real-time imaging to improve functionality.[24] Current research explore machine learning for flap perfusion assessment and robotic-assisted microsurgery along with use of predictive algorithms to reduce human error.[25] Ongoing studies are investigating AI's role in improving postoperative functional restoration through targeted rehabilitation protocols. Machine learning models such as deep neural networks are being trained to predict the success of vascularized flaps by analyzing preoperative imaging and patient-specific factors e.g., age, or related comorbidities. Da Vinci robot enable greater precision in flap dissection and suturing and now is being used for complication management and recovery time. AI-driven imaging tools such as indocyanine green (ICG) fluorescence imaging assess blood flow in real time to ensure adequate flap perfusion during surgery. Wearable sensors with AI algorithms track physiological parameters, for instance, oxygen levels, to detect early signs of complications which determine surgical risks before operations.[26,27]

CONCLUSIONS

From the above research, we can conclude artificial intelligence has become an important part of post-management of vascular flap reconstruction in abdominal surgeries by enhancing function restoration. We discussed it aids in monitoring tissue perfusion and early detection of complications like ischemia, necrosis, or thrombosis using real-time imaging and predictive analytics and AI algorithms analyze patient data to optimize recovery plans, personalize treatments, and adjust interventions for better outcomes. It is known that AI-driven models can improve surgical precision in vascular anastomosis while machine learning helps predict complications, guiding early interventions to improve flap viability and functional outcomes in abdominal reconstruction which accelerates recovery and minimizes post-operative complications.

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