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Artificial Intelligence In Perforator Flap Surgery: High Diagnostic Performance Across The Reconstructive Pathway But Persistent Barriers To Clinical Adoption

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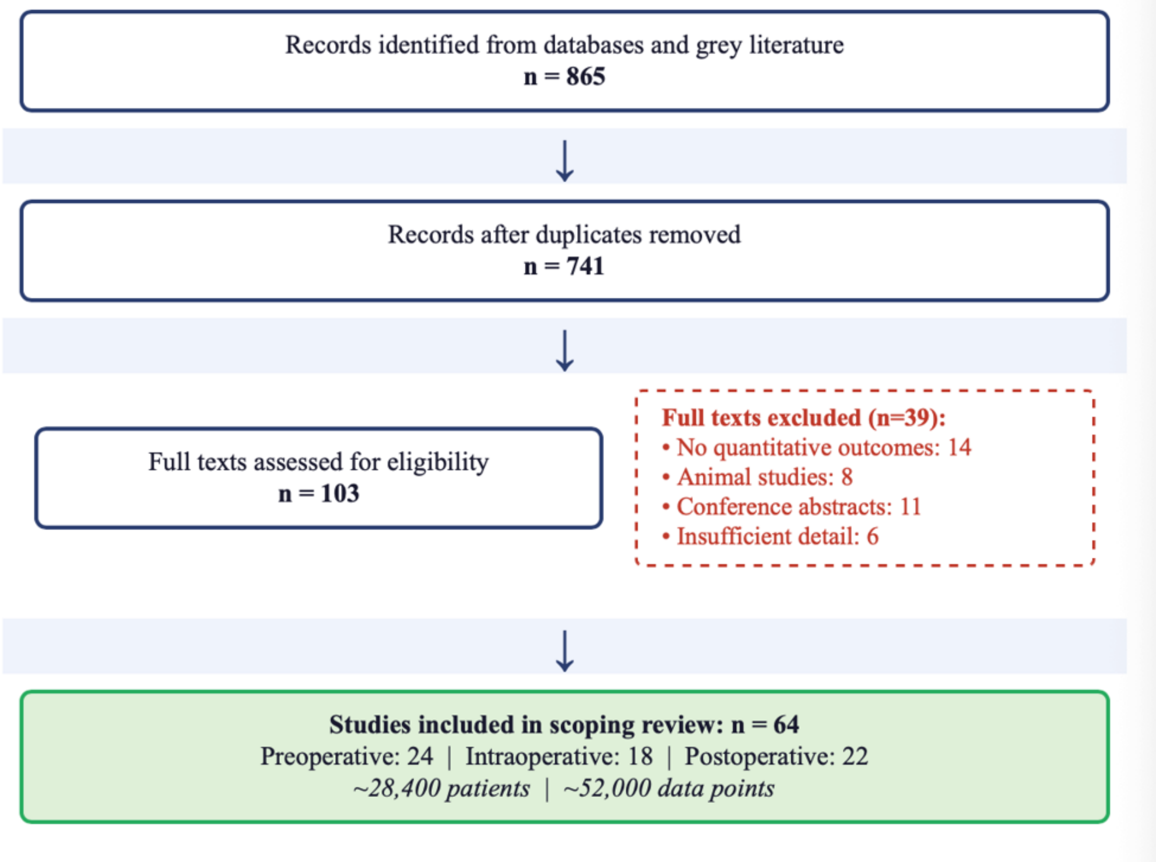
Abstract
Introduction: *Perforator flap surgery requires accurate preoperative vascular mapping, reliable intraoperative perfusion assessment, and early detection of postoperative vascular compromise. Artificial intelligence (AI) has emerged as a promising adjunct across the reconstructive pathway. Despite rapidly increasing publication volume and encouraging performance metrics, routine clinical adoption remains limited. This systematic scoping review evaluates the current evidence base for AI in perforator flap surgery and identifies barriers to implementation.*
Methods: *A PRISMA-ScR compliant systematic scoping review was conducted across MEDLINE, EMBASE, and Cochrane Library (January 2020 – May 2026). Sixty-four studies comprising approximately 28,400 patients met inclusion criteria.*



PRISMA-ScR Flow — Visual Summary

Results: *AI-assisted CT angiography reduced preoperative planning time by 85% (180 to 28 minutes per patient) with perforator identification sensitivity and specificity exceeding 93%. Intraoperatively, AI-assisted ICG fluorescence analysis achieved >99% perfusion zone classification accuracy, with an ischaemic threshold established at <22 grayscale units. Postoperatively, pooled analysis of 18,520 patients reported sensitivity 78%, specificity 88%, and AUROC 0.91; smartphone-based applications achieved 97.5% sensitivity for arterial insufficiency. Limitations included retrospective single-centre methodology (78% of studies), skin-tone dataset bias, and absent health-economic analysis.*

Conclusion: *AI demonstrates strong diagnostic performance across all phases of perforator flap surgery. Prospective multicentre validation and health-economic evaluation are required before routine NHS implementation can be recommended.*
Keywords: *Artificial intelligence; machine learning; perforator flap; free flap; microsurgery; reconstructive surgery; PRISMA-ScR*

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I. Introduction

Perforator flap surgery represents one of the most technically demanding domains within reconstructive plastic surgery. Successful outcomes depend on three critical phases: accurate preoperative vascular mapping to identify suitable perforator vessels, reliable intraoperative perfusion assessment to guide flap design and detect ischaemia, and vigilant postoperative monitoring to identify vascular compromise — a complication carrying a salvage rate of only 50–60% when reoperation is delayed beyond two hours.

Artificial intelligence (AI) — encompassing machine learning (ML), deep learning (DL), convolutional neural networks (CNNs), and generative adversarial networks (GANs) — has attracted substantial research interest across all three phases of the reconstructive pathway. Publication volume in this field grew from 37 papers in 2020 to over 300 in 2024, reflecting rapidly expanding scientific activity. AI applications now span CT angiography perforator mapping, intraoperative fluorescence angiography analysis, smartphone-based postoperative monitoring, and machine learning models for risk stratification and outcome prediction.

Despite these advances, routine clinical integration of AI in perforator flap surgery remains limited. Barriers include retrospective study designs, single-centre datasets, limited external validation, skin-tone bias in photographic models, regulatory challenges, and absence of health-economic analysis relevant to NHS implementation. No prior synthesis has comprehensively evaluated the diagnostic performance, clinical utility, and implementation barriers of AI across all three phases of perforator flap surgery.

This systematic scoping review aims to: (1) characterise the current evidence base for AI across the full perforator flap surgical pathway; (2) synthesise quantitative performance metrics for each application domain; and (3) identify key barriers and enablers to clinical adoption in reconstructive practice.

II. Methods

Study Design

A systematic scoping review was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR) guidelines (Tricco et al., 2018). Scoping review methodology was selected given the heterogeneity of AI modalities, study designs, and outcome measures, and the primary aim of mapping the breadth of the evidence base rather than synthesising a single pooled effect estimate.

Search Strategy

A comprehensive database search was conducted across MEDLINE/PubMed, EMBASE, and Cochrane Library from January 2020 to May 2026. Search terms included combinations of: "artificial intelligence", "machine learning", "deep learning", "neural network", "convolutional neural network", "perforator flap", "free flap", "microsurgery", "preoperative planning", "postoperative monitoring", "flap failure", "perforator mapping", "indocyanine green", "CT angiography", and "fluorescence angiography". Additional records were identified through grey literature searching, conference proceedings, and forward citation tracking.

Eligibility Criteria

Inclusion criteria:
- AI, ML, or DL application in perforator or free flap surgery
- Quantitative outcomes related to diagnostic accuracy, efficiency, complication prediction, or clinical utility
- English language publication

Exclusion criteria:
- Case reports involving fewer than five patients
- Animal studies without human translational data
- Conference abstracts without accompanying full quantitative data

Study Selection and Data Extraction

Following removal of 124 duplicates from 865 identified records, 741 unique records were screened by title and abstract. Of 103 full-text articles assessed for eligibility, 39 were excluded (no quantitative outcomes n=14; animal studies n=8; conference abstracts without data n=11; insufficient methodological detail n=6). Sixty-four studies met final inclusion criteria. Data were extracted on: study design, patient cohort size, AI modality, clinical application domain, performance metrics, and identified implementation barriers.

Quality Assessment

Diagnostic accuracy studies were appraised using the QUADAS-2 tool. Observational cohort studies were assessed using the Newcastle-Ottawa Scale. Given the scoping nature of this review, quality appraisal informed narrative synthesis rather than formal risk-of-bias weighting.

III. Results

Study Characteristics

Sixty-four studies comprising approximately 28,400 patients and 52,000 discrete data points met inclusion criteria. Studies were distributed across three application domains:

- Preoperative AI planning: 24 studies
- Intraoperative AI assessment: 18 studies
- Postoperative AI monitoring: 22 studies

The majority of included studies (78%) were retrospective single-centre investigations with limited external validation. The DIEP flap for breast reconstruction was the most frequently studied flap type, followed by the anterolateral thigh (ALT) flap and fibula free flap. Publication volume increased markedly across the review period, with a six-fold increase in AI-related reconstructive surgery publications between 2020 and 2024.

Preoperative AI Applications

Perforator Mapping and Vascular Planning

AI-assisted CTA analysis reduced preoperative planning time from a mean of 180 minutes to 28 minutes per patient (85% reduction), while achieving perforator identification sensitivity and specificity exceeding 93% against hand-held Doppler as the reference standard.

Mavioso et al. developed a computer vision algorithm for DIEP flap planning demonstrating millimetric accuracy while reducing radiologist analysis time from 2–3 hours to approximately 30 minutes per patient. Shen et al. applied a U-Net deep learning architecture for ALT flap planning, achieving superior consistency to manual methods. De La Hoz et al. demonstrated a radiation- and contrast-free perforator mapping alternative achieving >92% accuracy against Doppler-confirmed locations. Saxena et al. demonstrated AI vessel tree segmentation with >93% sensitivity and specificity, processing each CTA frame in under 0.2 seconds.

A fully automated DIEP flap segmentation framework employing Swin UNETR deep learning architecture was validated on 55 prospective cases, achieving a Dice similarity coefficient of 0.60 and 95th-percentile Hausdorff distance <18 mm, demonstrating clinical feasibility for standardised planning.

A combined AI and augmented reality approach for jaw reconstruction with fibula free flaps achieved 92.8% predictive accuracy for perforator location across 26 consecutive patients, with no intraoperative plan adjustments required.

Risk Stratification and Outcome Prediction

Machine learning models demonstrated significant promise for preoperative risk stratification:

- Asaad et al.: ML accuracy 63–98% for head and neck free flap failure prediction; smoking, vein graft use, and hypertension were dominant predictors
- O'Neill et al.: Obesity and smoking identified as principal predictors of total flap loss in >1,000 DIEP cases
- Myung et al.: 81% accuracy for donor-site complication prediction in 568 abdominal flap breast reconstruction patients
- Chartier et al.: BreastGAN (generative adversarial network) produced patient-specific postoperative simulations, reducing patient decisional conflict scores by 25% in a randomised study

Intraoperative AI Applications

Augmented Reality Navigation

Pietruski et al. demonstrated AR-guided fibula free flap harvest in mandibular reconstruction, achieving osteotomy accuracy within ≤3° angular and ≤2 mm positional error — comparable to patient-specific 3D-printed cutting guides with the added benefit of real-time intraoperative adjustability. Falola et al. described an AR microscope setup improving trainee depth perception and reducing fatigue, demonstrating significant surgical education potential.

AI-Assisted Perfusion Assessment

Singaravelu et al. applied ML to intraoperative ICG fluorescence angiography video analysis, achieving >99% accuracy in perfusion zone classification. Critically, a clinically actionable ischaemic fluorescence intensity threshold of <22 grayscale units was established — a reproducible, objective cut-off that could standardise intraoperative perfusion decision-making across centres.

Atkinson et al. evaluated large language models (LLMs) as intraoperative advisors for DIEP flap surgery; while responses were accurate, performance was judged comparable to resident-level knowledge and insufficient to replace consultant-level judgement in nuanced scenarios.

Postoperative AI Applications

Study	Application	Key Performance Metric
Kim et al. 2024	Smartphone AI flap monitoring	Sensitivity 97.5% (arterial), 92.8% (venous)
Hsu et al. 2023	iOS deep learning venous congestion app	~95% accuracy
Maktabi et al. 2025	Hyperspectral imaging + CNN	Sensitivity 70%, Specificity 76%
Puladi et al. 2023	ML transfusion prediction (H&N free flaps)	78% stratification accuracy
Pooled meta-analysis (12 studies, 18,520 patients)	Complication prediction	Sensitivity 78%, Specificity 88%, AUROC 0.91

Smartphone-based deep learning applications achieved 97.5% sensitivity for arterial insufficiency and 92.8% for venous insufficiency — performance exceeding published nurse-led clinical monitoring benchmarks. Pooled meta-analysis of 12 studies (18,520 patients) reported AUROC of 0.91, indicating excellent overall discriminatory performance for AI-based complication prediction.

Barriers to Clinical Adoption

The following barriers to AI implementation were consistently identified across included literature:

- **Retrospective methodology:** 78% of studies were retrospective and single-centre with limited external validation
- **Skin-tone dataset bias:** Photographic AI models showed measurable performance degradation in patients with Fitzpatrick skin types IV–VI
- **Device variability:** Differences in smartphone camera hardware adversely affected image-based monitoring algorithm performance
- **Workflow integration:** Most AI tools exist as standalone systems requiring separate data export/import steps
- **Regulatory barriers:** Absence of CE marking and NHS data governance frameworks for surgical AI
- **Health-economic evidence gap:** No included study reported formal NHS cost-effectiveness analysis

IV. Discussion

This systematic scoping review synthesises the most comprehensive evaluation of AI across all phases of perforator flap surgery to date, encompassing 64 studies, 28,400 patients, and 52,000 data points. AI demonstrates high diagnostic performance across preoperative planning, intraoperative perfusion assessment, and postoperative monitoring — with the critical caveat that most evidence derives from retrospective single-centre studies without prospective multicentre validation.

Preoperative Planning

The most immediately clinically translatable finding is in the preoperative domain. AI-assisted CTA analysis reduces planning time by 85% while maintaining diagnostic accuracy above 93%. In an NHS context, this represents a potential saving of approximately 152 minutes of consultant and radiologist time per operative case — a meaningful efficiency gain with direct resource implications at scale. The automated Swin UNETR segmentation framework, validated prospectively across 55 DIEP cases, represents a credible candidate for pilot implementation at UK reconstructive centres.

Intraoperative Assessment

The establishment of a reproducible, objective ischaemic fluorescence threshold (<22 grayscale units) for intraoperative ICG-AI analysis is a clinically significant finding. Currently, intraoperative perfusion assessment is entirely experience-dependent, introducing centre-level variability in flap design decisions. An objective, AI-derived threshold — if prospectively validated — would standardise this critical decision point and provide medicolegally defensible documentation of intraoperative perfusion assessment. This represents a high-priority target for prospective multicentre validation.

Postoperative Monitoring

The postoperative monitoring evidence is the most statistically robust, supported by pooled meta-analysis demonstrating AUROC of 0.91. Smartphone-based applications require no additional capital hardware investment and could be implemented across low-resource reconstructive units. The 97.5% sensitivity for arterial insufficiency detection significantly exceeds traditional nursing observation protocols in published comparisons. However, the skin-tone bias identified across photographic monitoring models must be resolved before equitable deployment across diverse patient populations can be assured.

Barriers to Implementation

The barriers identified in this review — retrospective designs, dataset bias, workflow fragmentation, regulatory uncertainty, and absent health-economic data — are consistent with challenges encountered in first-generation clinical AI adoption more broadly. The evidence base for AI in perforator flap surgery is substantial; the obstacles are infrastructural, regulatory, and economic rather than fundamentally scientific. Addressing these requires coordinated national investment in prospective multicentre trials, diverse and representative training datasets, and formal health technology assessment to establish cost-effectiveness thresholds relevant to NHS commissioning bodies.

Implications for Training

AR navigation and AI-assisted planning tools identified in this review carry significant implications for surgical education. AI perforator mapping overlays, deep learning perfusion analysis tools, and AR microscopy systems each offer novel simulation-based training modalities. National training programme directors should consider how AI-augmented tools can be formally integrated into the reconstructive surgery curriculum.

Limitations

This review carries several limitations. The heterogeneity of included studies — spanning multiple AI modalities, flap types, and outcome measures — precludes formal meta-analytic pooling beyond the postoperative domain. As a scoping review, risk-of-bias weighting was not applied to performance metric synthesis. Publication bias may overrepresent positive AI performance findings. Rapid publication growth during the review period means some included AI models may have been superseded by more recent architectures.

V. Conclusion

Artificial intelligence demonstrates high diagnostic performance across preoperative planning, intraoperative perfusion assessment, and postoperative monitoring in perforator flap surgery. AI-assisted CTA reduces planning time by 85% at >93% accuracy; intraoperative ICG-AI achieves >99% perfusion zone classification with an objective ischaemic threshold; and postoperative AI surveillance achieves AUROC 0.91 across 18,520 pooled patients.

Current barriers — retrospective methodology, dataset bias, workflow fragmentation, regulatory uncertainty, and absent health-economic data — limit widespread adoption. Prospective multicentre UK trials are warranted to establish clinical effectiveness, cost-effectiveness, and safe integration into routine NHS reconstructive practice. BAPRAS is uniquely positioned to coordinate this national effort and define the standard of AI-augmented reconstructive care.

Acknowledgements

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Ethics Statement

No ethical approval was required for this systematic scoping review. No patient-identifiable data were accessed.

Data Availability

All data supporting this review are available from the corresponding author upon reasonable request.

Prepared in accordance with PRISMA-ScR reporting guidelines (Tricco et al., 2018).

DECLARATIONS CONFLICT OF INTEREST STATEMENT The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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ETHICAL APPROVAL STATEMENT This systematic scoping review did not involve primary data collection, patient contact, or access to identifiable patient data. No ethical approval was required. The review was conducted in accordance with the PRISMA extension for scoping reviews (PRISMA-ScR) guidelines.

DATA AVAILABILITY STATEMENT No primary datasets were generated or analysed during this study. All data reviewed are available within the published literature cited in the reference list.