

Review article

Artificial Intelligence for Free Flap Monitoring in Reconstructive Surgery: A Review

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Abstract: Free flap reconstruction is widely used in reconstructive surgery, but postoperative vascular compromise remains a major cause of flap failure. Early detection of arterial insufficiency and venous congestion is essential for timely intervention and flap salvage. Conventional monitoring is limited by observer variability, flap accessibility, and assessment frequency. Artificial intelligence (AI) may support more consistent and continuous surveillance. This review examines the diagnostic performance, clinical utility, implementation challenges, and research priorities of AI-based postoperative free flap monitoring. Applications include smartphone photography, serial clinical images, thermal imaging, near-infrared spectroscopy, hyperspectral imaging, and other monitoring signals. Tasks encompass classification, segmentation, severity grading, and longitudinal prediction, distinguishing detection of existing perfusion abnormalities from prediction of subsequent compromise. Emerging studies report promising performance in identifying impaired perfusion; however, diagnostic accuracy alone does not establish clinical effectiveness. Limitations include small or single-center cohorts, image-level data leakage, class imbalance, inconsistent reference standards, limited external validation, and insufficient evidence of improved flap salvage. Performance may vary with flap location, tissue characteristics, skin pigmentation, image quality, and monitoring protocols. Intraoral and buried flaps pose additional accessibility challenges. Safe implementation requires standardized data acquisition, transparent alert thresholds, clinician oversight, privacy protection, and clear escalation pathways. AI may complement established clinical assessment, but routine adoption requires multicentre validation and prospective evidence of clinical benefit. Future studies should prioritize patient-level performance, detection time, false-negative events, unnecessary alerts, workload, flap salvage, and patient outcomes.

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Introduction

Microvascular free-flap reconstruction is an established technique in reconstructive surgery, providing a reliable way to restore complex tissue defects following cancer resection, trauma, infection and other surgical conditions. By transferring tissue with its vascular supply and reconnecting the blood vessels using microsurgical techniques, surgeons can reconstruct defects that cannot be adequately

managed with simpler methods [1]. Despite improvements in surgical techniques and perioperative care, successful reconstruction remains dependent on maintaining adequate blood flow after surgery. Postoperative vascular compromise, particularly arterial insufficiency and venous congestion, continues to be an important cause of flap morbidity and failure. Early recognition is therefore essential because timely intervention may allow the

underlying vascular problem to be corrected before irreversible tissue damage occurs [2].

Postoperative free-flap surveillance traditionally relies on repeated clinical examinations, supported when appropriate by handheld Doppler ultrasonography, implantable Doppler devices and tissue perfusion or oxygenation monitoring. These methods provide valuable information, but each has limitations [3]. Clinical examination depends partly on staff experience and the interpretation of visible findings, while device-based approaches measure specific physiological signals that may not fully represent the condition of the entire flap. Monitoring also requires repeated assessments over periods when clinical teams may be managing several patients simultaneously. These challenges have encouraged interest in technologies that can support more consistent assessment and help clinicians recognize concerning changes at an early stage [4].

AI, particularly machine learning and deep learning, offers new possibilities for analyzing postoperative monitoring data. Image-based models can examine photographs for changes in colour, texture, swelling and other visual characteristics associated with altered perfusion. Other approaches can process thermal images, tissue oxygenation measurements and optical signals to identify patterns that may be difficult to assess consistently through routine observation alone. Automated image acquisition and longitudinal analysis may also allow changes to be evaluated across successive observations rather than relying exclusively on isolated examinations [5]. Recent research has explored AI-assisted assessment of intraoral free flaps, including image classification and ordinal grading approaches intended to characterize flap condition more systematically. However, the clinical relevance of these methods depends on the quality of the underlying data, the reliability of their predictions and their performance under real postoperative conditions [6].

An important distinction must be made between diagnostic performance and clinical utility. A model may achieve high classification accuracy in a retrospective dataset without demonstrating that it detects vascular compromise earlier, reduces unnecessary interventions or improves flap salvage. Performance estimates may also be affected by small patient cohorts, imbalanced datasets, repeated images from the same patient, inconsistent reference standards and limited external validation [7]. Furthermore, visible flap changes can be influenced by anatomical location, postoperative swelling, lighting,

camera characteristics and other factors unrelated to vascular failure. These challenges raise questions about whether results obtained in one clinical setting can be generalized to different institutions, flap types and patient populations. The possibility of false-negative predictions is particularly important because a missed episode of vascular compromise may delay urgent clinical assessment [8].

The implementation of AI-assisted monitoring also involves practical and ethical considerations. Systems must fit existing postoperative workflows, provide interpretable and timely alerts, protect patient images and clinical information, and remain usable when acquisition conditions are suboptimal [9]. Staff must understand the intended role of the technology and retain the ability to override automated recommendations. Most importantly, AI outputs should support rather than replace clinical assessment, and suspected vascular compromise must receive urgent attention regardless of whether an algorithm identifies an abnormality [10].

This review critically examines the evidence for AI in postoperative free-flap monitoring in adult reconstructive surgery, with pediatric evidence considered separately where available. It evaluates the monitoring technologies and data sources used in current systems, the AI methods and prediction target they support, and the diagnostic performance and methodological quality of published studies [11]. It also examines whether reported technical achievements translate into meaningful clinical benefits, including earlier recognition of vascular compromise, timely intervention, flap salvage and reduced monitoring burden. Finally, the review considers generalizability, equitable performance, safety governance and implementation challenges, and identifies priorities for external validation and prospective clinical impact research [12]. By distinguishing promising technical developments from demonstrated clinical benefits, this review aims to clarify the current role of AI in free-flap surveillance and the evidence required before these systems can be integrated safely into routine reconstructive practice [13].

Clinical Problem and Current Surveillance

Postoperative monitoring is essential for maintaining the viability of microvascular free flaps after reconstructive surgery. Although advances in microsurgical techniques have improved surgical outcomes, vascular complications remain a major concern [14]. Arterial insufficiency and venous congestion are the two principal forms of vascular

compromise that can threaten flap survival. Their early recognition is important because delayed intervention may result in irreversible tissue damage, partial flap necrosis or complete flap loss. Consequently, reliable surveillance methods are needed to identify changes in perfusion and support timely clinical decision-making [15].

Arterial Insufficiency and Venous Congestion

Arterial insufficiency occurs when an inadequate volume of oxygenated blood reaches the transferred tissue. It may result from arterial thrombosis, vessel kinking, external compression or other problems affecting blood inflow [16]. Clinically, an affected flap may appear pale, feel cool and demonstrate delayed capillary refill. As oxygen delivery decreases, tissue viability becomes increasingly threatened. Venous congestion develops when blood cannot drain adequately from the flap, commonly because of venous thrombosis, compression or mechanical obstruction [17]. The resulting accumulation of blood may produce a bluish or purple appearance, swelling, increased tissue tension and unusually rapid capillary refill. Although these findings can help distinguish the two conditions, their presentation varies with flap type, anatomical location and the stage of vascular compromise. Arterial and venous abnormalities may also coexist, making assessment more challenging [18].

Conventional Monitoring Methods

Clinical examination remains a fundamental method of postoperative free-flap surveillance. It involves assessing colour, temperature, capillary refill, tissue turgor and, when appropriate, the response to pinprick testing [19]. Repeated examinations allow healthcare professionals to identify changes from the flap's baseline condition. However, interpretation may vary between observers, and monitoring requires trained staff to perform regular assessments, including during overnight shifts [20].

Handheld Doppler ultrasonography is commonly used to assess blood flow in accessible vessels. It provides a relatively simple bedside method for detecting vascular signals, but its reliability depends on operator experience, probe positioning and vessel accessibility [21]. Implantable Doppler devices offer continuous or near-continuous monitoring of blood flow at a selected vascular site. Nevertheless, signal loss, technical problems and the inability to assess the entire tissue directly may limit interpretation. A detectable vascular signal does not necessarily confirm adequate perfusion throughout the flap [22].

Tissue oxygenation monitoring provides additional physiological information. Near-infrared spectroscopy, for example, estimates tissue oxygen saturation and may help identify changes associated with impaired perfusion [23]. Other optical techniques can assess tissue oxygenation and microvascular characteristics. However, measurements may be influenced by probe placement, tissue composition, oedema and device-specific limitations. These methods therefore complement rather than replace clinical examination [24].

Potential Role of Artificial Intelligence

AI may support postoperative surveillance by analyzing repeated photographs or physiological measurements and identifying patterns associated with vascular compromise. Automated systems could help standardize assessments, track changes over time and alert staff when observations require further evaluation [25]. However, promising classification performance does not establish that an AI system improves flap salvage or reduces flap loss. False-positive alerts may increase workload, while false-negative results could delay recognition of a serious complication [26].

Therefore, AI-assisted monitoring should be regarded as an adjunct to established surveillance methods. Any concerning clinical finding requires prompt assessment by the surgical team, regardless of the algorithm's output. Suspected vascular compromise must be managed according to clinical urgency, without waiting for automated confirmation. The ultimate value of AI depends not only on its diagnostic performance but also on whether it supports faster, safer and more effective clinical decisions [27].

Data Sources and Monitoring Technologies

AI systems for free-flap monitoring depend on the quality, type and consistency of the data collected after surgery. Different monitoring technologies capture different aspects of flap condition, including visible tissue changes, surface temperature, oxygenation and microvascular perfusion [28]. Understanding these differences is important because an algorithm can only interpret the information provided by its input source. The monitoring device and the AI model must therefore be evaluated separately when assessing diagnostic performance and clinical usefulness [29].

Smartphone Photographs and Serial Clinical Images

Smartphone photography offers a practical and relatively inexpensive method for documenting the external appearance of accessible free flaps. Images can capture changes in colour, swelling and tissue texture that may indicate impaired circulation [30]. Machine learning models can classify these images as normal or abnormal, while image segmentation techniques can identify the flap region for more focused analysis. Serial photographs also allow changes to be assessed over time rather than relying on a single observation [31].

However, image quality can be affected by lighting, camera specifications, viewing angle, distance and motion. Changes in exposure or white balance may alter apparent tissue colour without reflecting a genuine physiological change. These issues are particularly important for intraoral flaps, where saliva, blood contamination and limited access may obscure the tissue surface. Standardized image acquisition and quality checks are therefore necessary for reliable analysis [32].

Thermal Imaging

Thermal imaging measures infrared radiation emitted from the tissue and produces a map of surface temperature. Changes in temperature may reflect alterations in blood flow or tissue perfusion, making thermal images a potential source of information for AI-based monitoring. Algorithms can analyse temperature patterns and identify changes that warrant further examination [33].

Nevertheless, surface temperature is influenced by ambient conditions, distance from the camera, airflow and recent contact with the tissue. Thermal abnormalities are not specific to vascular compromise, so findings require interpretation alongside clinical information. Consistent acquisition conditions are important when comparing images collected at different postoperative time points [34].

Near-Infrared Spectroscopy and Hyperspectral Imaging

Near-infrared spectroscopy (NIRS) estimates tissue oxygen saturation using the absorption of remeasurements may help identify changes in oxygen delivery. AI models can analyze these measurements to detect concerning trends or classify physiological patterns. However, NIRS is the underlying monitoring

technology; AI is an additional analytical component that interprets its output [35].

Hyperspectral imaging captures information across multiple wavelengths, allowing tissue oxygenation and other perfusion-related characteristics to be estimated. Although this approach may provide detailed information about superficial tissue, its performance depends on acquisition quality, image processing and suitable reference standards [36].

Acquisition Challenges and Buried Flaps

Monitoring frequency influences the ability to detect rapid changes. Infrequent measurements may miss transient abnormalities, whereas frequent acquisition can increase data volume, computational demands and false alarms [37]. Motion, inconsistent positioning and environmental interference can further reduce reliability. Buried flaps present an additional challenge because their tissue surface cannot be directly photographed or examined. External imaging methods are therefore unsuitable unless an accessible monitoring window or another measurable signal is available [38].

Overall, AI-assisted surveillance requires standardized data collection, appropriate quality control and validation under real clinical conditions. Combining complementary data sources may improve assessment, but multimodal systems also introduce greater technical complexity and implementation costs [39].

AI Methods and Prediction Targets

AI systems for postoperative free-flap monitoring use different computational approaches depending on the type of data available and the clinical question being addressed. These approaches include image classification, image segmentation, ordinal grading and longitudinal change detection. Although they may be used together, each method serves a different purpose and requires appropriate validation before clinical application [40].

Image Classification and Segmentation

Image classification assigns an image to a predefined category, such as normal perfusion, arterial insufficiency or venous congestion. Deep learning models, particularly convolutional neural networks, can learn visual patterns associated with these categories from labelled clinical images [41]. Their performance depends on the quality and diversity of the training data and their ability to distinguish

genuine physiological changes from variations caused by lighting, camera settings or postoperative swelling [42].

Table 1. Monitoring modalities, measured signals, intended applications and limitations in postoperative free-flap surveillance.

Monitoring modality	Signal measured	Intended use in free-flap monitoring	Key limitations
Clinical examination	Colour, temperature, capillary refill, tissue turgor and pinprick response	Identifying clinical signs of arterial insufficiency or venous congestion	Observer variability, dependence on clinical experience and need for repeated assessments
Handheld Doppler ultrasonography	Blood-flow signal from accessible vessels	Assessment of vascular flow and investigation of suspected vascular compromise	Operator dependence, sensitivity to probe positioning, and limited ability to assess overall tissue perfusion
Implantable Doppler	Blood-flow signal from a monitored vessel, commonly near the vascular anastomosis	Continuous or near-continuous surveillance of vascular flow	Signal loss, technical failure and inability to directly assess the entire flap
Smartphone photography and serial clinical images	Visible colour, texture, swelling and changes in tissue appearance	AI-based image classification, segmentation and longitudinal change detection	Lighting variation, camera differences, motion, image quality and contamination
Thermal imaging	Infrared radiation and surface temperature distribution	Identifying temperature patterns that may accompany changes in perfusion	Environmental influences, limited specificity and sensitivity to acquisition conditions
Near-infrared spectroscopy (NIRS)	Estimated tissue oxygen saturation based on near-infrared light absorption	Monitoring changes in tissue oxygenation that may indicate impaired perfusion	Device-dependent measurements, probe placement, tissue characteristics and limited spatial coverage
Hyperspectral imaging	Wavelength-dependent reflected light used to estimate tissue oxygenation and perfusion-related characteristics	Mapping superficial tissue characteristics and identifying potentially abnormal perfusion patterns	Equipment cost, acquisition complexity, motion sensitivity and need for clinical validation
AI-assisted multimodal monitoring	Combined image features and/or physiological measurements from multiple sources	Integrating complementary signals to support risk assessment and clinical alerts	Greater technical complexity, synchronization requirements, missing data and limited evidence of improved patient outcomes

Image segmentation identifies the specific pixels belonging to a flap or a relevant tissue region. This allows an algorithm to focus on the area of interest rather than the surrounding skin, surgical dressings or background. Segmentation can support more consistent colour analysis and facilitate the extraction of features used by subsequent classification models.

However, inaccurate segmentation may affect the final prediction, particularly when flap boundaries are unclear or the image contains contamination [43].

Ordinal Grading and Longitudinal Change Detection

Ordinal grading classifies flap condition according to ordered severity levels rather than assigning only normal or abnormal labels. For example, a grading system may distinguish healthy tissue from mild, moderate and severe abnormalities. This approach may provide clinically useful information about the degree of concern, although the categories must be clearly defined and reproducible between assessors [44].

Longitudinal change detection evaluates measurements or images collected from the same patient over time. Instead of assessing each observation independently, these methods examine trends such as progressive colour changes, declining tissue oxygenation or evolving temperature patterns. This is potentially valuable because deterioration may be more apparent through comparison with an individual flap's baseline than through a single measurement. Nevertheless, missing observations, inconsistent acquisition conditions and normal postoperative changes can complicate interpretation [45].

Current Malperfusion Versus Future Flap Failure

An important distinction concerns the prediction target. Detecting current malperfusion means identifying evidence of impaired blood supply at the time of assessment. Predicting subsequent flap failure involves estimating whether a flap that may currently appear viable will deteriorate later. The latter requires longitudinal data and clearly defined prediction intervals. A model developed to classify existing abnormalities should not automatically be described as predicting future failure [46].

Reference Standards and Label Quality

AI performance depends heavily on how training and evaluation labels are established. Labels based on surgeon assessment may reflect routine clinical judgment but can vary between observers. Operative findings, such as confirmed thrombosis or vascular obstruction, provide more direct evidence of a complication but may be available only for patients undergoing re-exploration. Treatment decisions and eventual flap outcomes can provide additional information, although neither necessarily establishes the precise physiological condition at an earlier time point [47].

These differences can introduce misclassification and verification bias. Therefore, studies should describe their reference standards, timing of assessments and criteria for defining compromise. Reliable labels are essential for determining whether an AI model recognizes clinically meaningful vascular abnormalities rather than simply reproducing subjective assessments [48].

Diagnostic Performance and Methodological Quality

Evaluating the diagnostic performance of AI systems is essential for determining their reliability in postoperative free-flap monitoring. Although high classification accuracy may indicate promising technical performance, it does not necessarily demonstrate that a model can identify vascular compromise safely in clinical practice. Studies should therefore report clearly defined performance measures alongside sufficient information about their datasets, validation methods and clinical reference standards [49].

Diagnostic Performance Measures

Sensitivity measures the proportion of compromised flaps correctly identified by a model, whereas specificity measures the proportion of unaffected flaps correctly classified as normal. Both are important, but sensitivity deserves particular attention because false-negative results may delay urgent intervention. Positive and negative predictive values provide additional information about the likelihood of compromise following a positive or negative prediction. However, these values depend on the prevalence of vascular complications in the evaluated population [50].

Confidence intervals should accompany performance estimates to show their statistical uncertainty, particularly when studies include small numbers of patients or complications. Calibration is also important because it indicates whether predicted probabilities correspond to observed risks. Where available, time to detection should be reported to establish whether AI identifies deterioration earlier than conventional surveillance. A model with high sensitivity may still have limited clinical value if its alerts occur too late to influence management [51].

Dataset Size and Class Imbalance

Free-flap failure is relatively uncommon compared with uncomplicated postoperative recovery.

Consequently, datasets may contain many normal images but few examples of arterial insufficiency, venous congestion or subsequent flap failure. This class imbalance can produce misleadingly high overall accuracy because a model may perform well on the majority class while missing clinically important abnormalities [52].

Studies should report both patient-level and image-level denominators, including the number of patients, flaps, images and confirmed complications. These units are not interchangeable because multiple images may originate from a single patient. Reporting only the total number of images can exaggerate the apparent size and diversity of the evidence base [53].

Data Leakage and Validation

Data splitting is another important methodological consideration. When images from the same patient appear in both training and testing datasets, a model may learn patient-specific characteristics rather than patterns that generalize to new patients. This data leakage can inflate performance estimates. Whenever possible, datasets should therefore be separated at the patient level, with additional external validation performed using patients from different institutions or clinical settings [54].

External validation is particularly important because cameras, lighting conditions, flap types and monitoring protocols vary between hospitals. Performance obtained from a single institution should not automatically be assumed to apply elsewhere [55].

Ungradable Images and Clinical Reliability

Studies should explain how they handle blurred, poorly illuminated, contaminated or otherwise ungradable images. Excluding these observations without reporting their frequency may overestimate real-world performance. Systems should be evaluated for their ability to recognize inadequate input and request reassessment rather than generating an unreliable prediction [56].

Overall, rigorous methodological reporting is necessary to distinguish genuine diagnostic capability from optimistic estimates produced by biased datasets or weak validation. Clinical readiness requires evidence that AI can detect important complications reliably across representative patients and realistic monitoring conditions [57].

Clinical Utility and Workflow Integration

The clinical value of AI in postoperative free-flap monitoring depends on whether it improves patient care rather than simply producing accurate predictions. Although promising diagnostic performance may support further development, its practical benefit must be assessed through clinically meaningful outcomes, including earlier recognition of vascular compromise, faster surgical assessment, timely re-exploration and improved flap salvage. Evidence concerning these outcomes remains essential before AI-assisted monitoring can be considered a reliable component of routine reconstructive practice.[40]

Clinical Outcomes and Alert Performance

A clinically useful monitoring system should identify concerning changes early enough to influence management. Studies should therefore measure the interval between an automated alert and clinical review, as well as the time from recognition of compromise to re-exploration when required. Flap salvage, partial or total flap loss, unnecessary interventions and length of hospital stay may provide additional information about clinical benefit. However, these outcomes are influenced by several factors, including the severity of vascular compromise, the timing of presentation and the availability of experienced surgical teams [58].

False-positive alerts also require careful evaluation. Frequent unnecessary alerts may increase staff workload, contribute to alert fatigue and reduce confidence in the monitoring system. Conversely, false-negative predictions may provide false reassurance and delay urgent assessment. Research should therefore examine both the benefits and potential harms of automated alerts rather than focusing exclusively on sensitivity or overall accuracy [59].

Different Levels of Clinical Evaluation

The design of a study determines how confidently its findings can be interpreted. Retrospective studies analyze previously collected images or monitoring records and may establish technical feasibility, but they cannot reliably demonstrate that AI improves real-time clinical decisions. Retrospective simulation studies can estimate how an alert system might perform using historical data; however, simulated alerts do not reproduce the full complexity of clinical practice [60].

Silent prospective testing evaluates an AI system using newly collected clinical data without displaying its predictions to the treating team. This approach can assess performance under realistic acquisition conditions while avoiding direct influence on patient management. Nevertheless, it cannot establish whether clinicians respond appropriately to alerts or whether their use improves outcomes [61].

Studies in which clinicians receive and act on AI-generated alerts provide more direct evidence of clinical utility. Ideally, these evaluations should compare relevant outcomes with those obtained through standard surveillance. However, differences in patient characteristics, staffing, monitoring frequency and institutional protocols may affect the results. Comparative designs should account for these factors when interpreting apparent improvements in care [62].

Integration into Clinical Workflows

Successful implementation requires AI systems to fit existing postoperative monitoring routines. Alerts

should reach the appropriate clinical staff promptly, communicate the level of concern clearly and allow clinicians to review the supporting observations. Systems must also function reliably during overnight shifts and periods of high workload. Training, technical support and procedures for device failure are important components of implementation [63].

Interpretation must also account for conventional monitoring and co-interventions. If AI is introduced alongside more frequent clinical examinations, additional Doppler assessments or changes in staffing, improved outcomes cannot automatically be attributed to the algorithm alone [64].

Ultimately, prospective impact studies are needed to determine whether AI-assisted surveillance improves timely intervention and flap salvage without creating excessive false alarms or workload. Until such benefits are demonstrated, AI should complement established monitoring methods rather than replace clinical judgment or urgent surgical assessment [65].



Figure 1. acquisition-to-alert-to-clinical-review workflow.

Generalizability and Equitable Performance

The clinical reliability of AI for free-flap monitoring depends on its ability to perform consistently across different patients, anatomical sites, flap types and healthcare settings. A model developed using a limited dataset may achieve encouraging results under

controlled conditions but perform less reliably when introduced into a different clinical environment. Evaluating generalizability is therefore essential to determine whether AI systems can support safe and equitable postoperative surveillance [66].

Anatomical Site and Flap Type

Free flaps used in head and neck reconstruction may differ considerably in appearance, tissue composition and accessibility. An external skin paddle can usually be photographed directly, whereas an intraoral flap may be difficult to assess because of restricted access, saliva, blood contamination and variations in lighting. These differences affect image quality and the visual features available to an algorithm. Consequently, performance demonstrated in extraoral flaps should not automatically be assumed to apply to intraoral reconstruction [67].

Flap composition also matters. Skin, muscle and composite tissue flaps may exhibit different surface characteristics and responses to changes in perfusion. Buried flaps present an additional challenge because their tissue cannot be assessed directly through conventional photography. Systems intended for these cases may require implantable monitoring devices or other physiological measurements. Studies should therefore report anatomical site, flap type and monitoring modality clearly and evaluate performance within clinically relevant subgroups [68].

Skin Pigmentation and Postoperative Changes

Skin pigmentation may influence the visibility of colour changes associated with arterial insufficiency or venous congestion. If training datasets disproportionately represent particular skin tones, image-based models may learn patterns that are less reliable in underrepresented populations. This could result in unequal sensitivity and delayed recognition of complications [69]. Researchers should include diverse patient populations and assess performance across skin pigmentation groups rather than assuming that a model performs equally well for everyone.

Postoperative oedema, bruising, dressings and changes in tissue appearance may also affect predictions. These findings can occur during normal recovery but may resemble features associated with vascular compromise. A robust model must distinguish relevant perfusion changes from common postoperative variation wherever possible. Repeated assessment against an individual patient's baseline may help, although its benefit requires clinical validation [70].

Equipment and Institutional Differences

Variations in camera resolution, image processing, lighting and acquisition distance can alter the appearance of photographs. Similarly, physiological monitoring devices may differ in their measurement

methods and output characteristics. Institutional differences in examination frequency, staff experience, alert thresholds and intervention protocols can further influence model performance and reported outcomes [71].

External validation should therefore include data from independent hospitals, different devices and diverse clinical workflows. Development cohorts should be compared with the intended patient population in terms of demographics, flap characteristics, complication frequency and acquisition conditions. Researchers should also report subgroup results and identify populations for which evidence remains insufficient [72].

Overall, generalizability cannot be established solely through strong performance in a single development dataset. Diverse training data, standardized acquisition procedures and independent validation are needed to determine whether AI-assisted monitoring remains reliable across clinical settings. Equitable implementation will require continued evaluation to ensure that technological benefits are not limited to the patients or institutions best represented in the original research [73].

Safety Governance and Future Research

The implementation of AI in postoperative free-flap monitoring requires careful attention to patient safety, data governance and clinical accountability. Although automated systems may support earlier recognition of vascular compromise, their use introduces risks related to inaccurate predictions, inappropriate alerts and technical failure. These concerns are particularly important in reconstructive surgery, where delays in recognizing vascular complications can have serious consequences. Future research should therefore evaluate not only diagnostic performance but also the safety, reliability and practical suitability of AI-assisted monitoring [74].

Privacy, Consent and Accountability

Photographs and other monitoring data may contain identifiable patient information, particularly when images include facial features or distinctive anatomical details. Appropriate consent procedures, secure data storage and controlled access are important when collecting images for AI development or clinical use. Researchers should also explain how data may be used, whether they will be shared with external organizations and how long they will be retained. Cybersecurity measures are necessary to reduce the

risks of unauthorized access, data loss and interference with connected monitoring systems [75].

Clinical accountability must also be clearly defined. AI-generated predictions should not be treated as independent clinical decisions, and responsibility for assessing suspected vascular compromise must remain within the established clinical care pathway. Systems should communicate uncertainty and limitations clearly enough for healthcare professionals to interpret their outputs appropriately. Clinicians should retain the ability to override automated recommendations when clinical findings or patient circumstances indicate a different course of action [76].

Device Failure and Safe Clinical Practice

AI-assisted monitoring may be affected by software errors, connectivity problems, poor-quality images or failure of the underlying monitoring device. A system that cannot obtain reliable input should identify the problem rather than generate an apparently reassuring prediction [77]. Fallback procedures should allow conventional surveillance to continue when automated monitoring becomes unavailable. Suspected vascular compromise must still receive urgent surgical assessment, regardless of whether the AI system is functioning or has generated an alert [78].

Priorities for Future Research

Future investigations should begin with multicentre external validation using independent patient cohorts, different monitoring devices and diverse clinical environments. These studies should assess whether

diagnostic performance remains consistent across flap types, anatomical sites and patient populations. Transparent reporting of patient numbers, complication rates, reference standards, missing data and ungradable observations would also improve the comparability of findings [79].

Following external validation, prospective studies should evaluate clinical impact under real postoperative conditions. Where feasible, comparative designs should examine whether AI-assisted monitoring improves alert-to-review time, time to re-exploration and flap salvage compared with standard surveillance. Partial and total flap loss, false-negative detection, unnecessary escalation, false-positive alerts and staff workload should also be measured. These outcomes are proposed research priorities rather than established benefits of AI [80].

Researchers should additionally assess calibration, usability, cost and the consequences of incorrect predictions. Long-term studies may help determine whether clinicians continue to respond appropriately to alerts and whether system performance changes after implementation. Together, these investigations could establish whether AI provides measurable benefits beyond existing monitoring methods [81].

Ultimately, the safe integration of AI into reconstructive surgery will depend on rigorous validation, transparent governance and evidence of meaningful clinical benefit. Until such evidence becomes available, AI should remain a supportive technology that complements established surveillance and preserves timely access to expert surgical assessment [82].

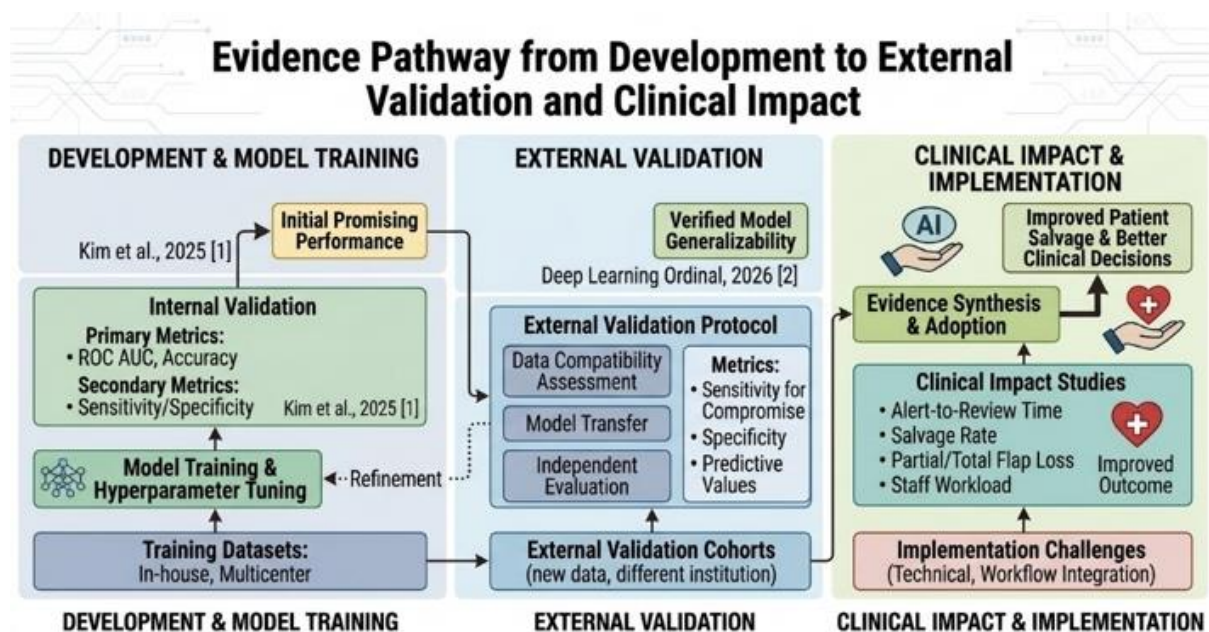


Figure 2. Evidence pathway from development to external validation and clinical impact.

Conclusion

Artificial intelligence has the potential to improve postoperative free flap monitoring by supporting the early recognition of vascular compromise, standardizing image interpretation, and identifying changes that may be difficult to detect through intermittent clinical assessment alone. Emerging studies have reported promising results in image-based classification and perfusion assessment. However, high diagnostic accuracy should not be interpreted as evidence of improved clinical outcomes. Current research remains limited by retrospective designs, relatively narrow patient populations, potential data leakage, inconsistent reference standards, and insufficient external validation. Evidence demonstrating reductions in time to intervention, flap loss, or unnecessary re-exploration remains limited.

The clinical value of AI will depend on its ability to perform reliably across different institutions, flap types, tissue characteristics, imaging conditions, and patient populations. Particular attention is required for intraoral and buried flaps, where direct visual assessment may be difficult or impossible. AI systems should therefore complement, rather than replace, established clinical examination and appropriate monitoring technologies. Safe implementation also requires clear alert thresholds, clinician oversight, data protection, and predefined escalation pathways.

Future research should prioritize prospective multicentre validation, patient-level diagnostic performance, and studies assessing the effects of AI-assisted monitoring on clinical decision-making and patient outcomes. By addressing these methodological and practical challenges, AI may become a valuable adjunct to free flap surveillance and contribute to safer and more consistent postoperative care.

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