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Artificial Intelligence–Enabled Multidisciplinary Surgical Care: Integrating Laboratory Diagnostics, Radiology, Pharmacy, Nursing, Operating Room Practice, and Oral–Maxillofacial Surgery

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Abstract
Artificial intelligence (AI) is reshaping surgical care across multiple disciplines, yet integration remains fragmented. This narrative review synthesizes evidence (2016–2024) on AI applications spanning laboratory diagnostics, radiology, pharmacy, nursing, operating room practice, and oral–maxillofacial surgery. AI enhances laboratory quality control and predictive analytics, improves radiological segmentation and three-dimensional surgical planning, supports perioperative medication safety through clinical decision support, augments nursing surveillance and operating room teamwork, and demonstrates diagnostic and prognostic utility in oral–maxillofacial surgery. However, translation is constrained by data heterogeneity, algorithmic opacity, workflow misalignment, and absent integration architectures. Central command suite concepts offer a unifying framework. This review argues that AI should function as a connective layer across surgical disciplines, preserving clinician oversight while enabling multidisciplinary data synthesis and real-time decision support.

Keywords: artificial intelligence; multidisciplinary surgical care; clinical decision support; oral–maxillofacial surgery; perioperative medicine.

Introduction
Surgical care is inherently multidisciplinary. A single patient journey—from preoperative assessment through intraoperative intervention to postoperative recovery—engages laboratory medicine, radiology, pharmacy, nursing, operating room personnel, and surgical specialists, each contributing distinct data streams and expertise. Historically, these domains have operated as semi-autonomous silos, with information exchanged through fragmented records and asynchronous communication. The consequences are well documented: diagnostic delays, medication errors, redundant testing, and suboptimal team coordination (Varghese et al., 2024; Ahmad et al., 2020). Artificial intelligence (AI) offers a mechanism to bridge these silos by processing multimodal data, generating actionable predictions, and supporting real-time clinical decisions across disciplinary boundaries.

Recent reviews have documented AI's transformative potential in individual surgical specialties. In oral and maxillofacial surgery (OMFS), AI has been applied to lesion detection, orthognathic planning, and risk prediction with promising accuracy (Siddiqui et al., 2022; Yan et al., 2021). In laboratory medicine, machine learning enhances pre-analytical sample management, analytical quality control, and post-analytical reporting (Xie et al., 2024). Radiological AI enables automated segmentation and three-dimensional visualization for surgical simulation (Zeng et al., 2024). Perioperative medication safety is being augmented by computerized decision support and predictive risk models (Paiste et al., 2024). Operating room nursing is beginning to incorporate intelligent monitoring and robotic scrub nurse concepts (Fischer, 2024). Yet the literature remains discipline-specific; few studies examine how these applications interact within a unified multidisciplinary framework.

This review addresses that gap. Its objective is to synthesize current evidence on AI-enabled multidisciplinary surgical care, with emphasis on

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integration mechanisms, shared challenges, and the conditions under which AI can function as a connective layer across laboratory diagnostics, radiology, pharmacy, nursing, OR practice, and OMFS. The review is narrative in design, drawing on peer-reviewed literature published between 2016 and 2024, and is intended for clinicians, health informatics researchers, and surgical policymakers navigating the translation of AI from bench to bedside.

2. Artificial Intelligence in Laboratory Diagnostics for Surgical Care

Laboratory diagnostics constitute the informational foundation of surgical decision-making. Preoperative coagulation profiles, inflammatory markers, renal function, and tumor markers inform risk stratification and operative planning. Intraoperative laboratory data—including point-of-care testing for hemoglobin, electrolytes, and glucose—guide transfusion and fluid management. Postoperative laboratory monitoring detects complications such as infection, acute kidney injury, and metabolic derangement. AI is reshaping each of these phases.

In the pre-analytical phase, computer vision and natural language processing are applied to sample identification, labeling verification, and rejection classification. Automated systems reduce human error in sample handling and improve chain-of-custody integrity (Xie et al., 2024). Reinforcement learning optimizes sample organization and retrieval within laboratory information systems, reducing turnaround times—a critical parameter in time-sensitive surgical pathways.

The analytical phase has seen substantial AI integration. Machine learning algorithms for daily quality control employ pattern recognition to detect deviations before they breach acceptable limits, moving laboratory quality management from reactive to predictive (Xie et al., 2024). Deep learning–based anomaly detection identifies analytical errors in real time, minimizing the risk of misreported results that could adversely affect surgical decisions. Predictive maintenance models forecast instrument failures, reducing unplanned downtime in laboratories serving high-volume surgical services.

Post-analytical AI applications directly influence surgical care. Natural language processing–driven report generation standardizes laboratory reporting and reduces transcription errors. AI clinical decision support systems (CDSS) interpret laboratory panels in context, flagging values that warrant surgical team notification. Rule-based critical alert systems ensure timely communication of life-threatening results, such as severe hyperkalemia or critically low hemoglobin, to the responsible surgical or anesthesia team (Xie et al., 2024).

A particularly promising development is the emergence of AI-assisted intraoperative molecular diagnostics. Investigational systems have demonstrated the capacity to classify brain tumors from imaging data in the operating room, potentially reducing reliance on frozen-section pathology and enabling real-time surgical margin assessment (Williams et al., 2021). AI-assisted stimulated Raman molecular cytology has shown accuracy in intraoperative surgical margin assessment for pancreatic ductal adenocarcinoma. These technologies represent a convergence of laboratory medicine and surgical practice, collapsing the temporal gap between tissue sampling and diagnostic information.

However, laboratory AI faces persistent challenges. Data quality remains a rate-limiting factor; machine learning models trained on incomplete or inconsistently annotated laboratory datasets produce unreliable outputs (Hussain et al., 2022). Interoperability between laboratory information systems and surgical informatics platforms is often inadequate, preventing seamless data flow. Regulatory frameworks for AI-based laboratory diagnostics are still maturing, and external validation studies are scarce. For surgical teams to trust laboratory AI outputs, the models must demonstrate robust performance across diverse patient populations and clinical contexts.

3. Artificial Intelligence in Radiology and Surgical Planning

Radiology is arguably the most mature domain of AI application in surgical care. Preoperative imaging—computed tomography (CT), magnetic resonance imaging (MRI), cone-beam CT (CBCT), and ultrasound—generates volumetric datasets that inform surgical approach, resection extent, and implant selection. AI enhances each stage of the radiological workflow, from image acquisition through interpretation to surgical simulation.

Automated image segmentation is among the most clinically impactful applications. Deep learning algorithms delineate anatomical structures—vessels, nerves, bones, and tumors—with accuracy approaching or exceeding that of expert radiologists in selected tasks. In image-guided spinal surgery, AI-assisted three-dimensional reconstruction and intraoperative registration have demonstrated improvements in lesion visualization and operative time reduction (Zeng et al., 2024). These capabilities directly support surgical planning, where accurate anatomical delineation reduces operative time and perioperative morbidity.

Three-dimensional reconstruction and surgical simulation represent a second major application area. AI-based systems convert two-dimensional imaging data into three-dimensional models, enabling virtual surgical planning and rehearsal. In urologic surgery, AI reconstruction of three-dimensional models of patient anatomy from CT or MRI scans enables clinicians to visualize structures and accurately plan surgical approaches (Khizir et al., 2024). In thoracic surgery, AI-enhanced three-dimensional reconstructions have been associated with a reduction in surgical approach errors of approximately 41% (MacLeod et al., as cited in Artificial Intelligence in Surgery, 2024).

In OMFS, radiological AI is integral to diagnosis and treatment planning. CBCT-based bone assessment and implant planning are supported by automated landmark detection and surgical simulation in orthognathic surgery (Siddiqui et al., 2022). AI models predict surgical difficulty and inferior alveolar nerve injury risk in impacted third molar surgery, enabling risk-stratified surgical planning. Classification of temporomandibular joint disorders from imaging data is another emerging application. These capabilities are particularly valuable in OMFS because the specialty relies heavily on subtle imaging patterns and borderline diagnostic categories, where interobserver variability remains a persistent challenge even among experienced clinicians (Ren et al., 2021).

A central challenge in radiological AI is generalizability. Most published models are trained and validated on single-center, retrospective datasets with limited demographic and technical diversity (Zeng et al., 2024; Ahmed et al., 2021). External validation across scanners, protocols, and patient populations is essential before widespread clinical adoption. Furthermore, the "black box" nature of many deep learning models undermines clinician trust. Explainable AI (XAI) techniques—including saliency maps, feature attribution, and similarity classification—are increasingly recognized as prerequisites for clinical integration (Zhang et al., 2022). Table 1 summarizes representative AI applications across the six disciplines, with evidence of performance and integration readiness.

Table 1. Representative AI Applications Across Multidisciplinary Surgical Care Domains

Domain	AI Application	Representative Performance Evidence	Integration Readiness
Laboratory diagnostics	Predictive QC; anomaly detection; intraoperative molecular classification	ML-based QC improves error detection; AI-assisted Raman cytology enables margin assessment (Xie et al., 2024)	Moderate; interoperability gaps
Radiology	Automated segmentation; 3D reconstruction; surgical planning	AI-assisted 3D reconstruction improves lesion visualization and reduces operative time (Zeng et al., 2024); 41% reduction in approach errors in thoracic surgery	High for segmentation; moderate for simulation
Pharmacy	Perioperative medication CDSS; ML-based prescription optimization	CDSS reduced medication errors (OR 0.33, 95% CI 0.30–0.36); CDSS reduced OR errors by up to 95% (Cai et al., 2024)	Moderate; workflow integration required
Nursing / OR	Robotic scrub nurse concepts; AI teamwork coaching; intelligent monitoring	Bibliometric emergence of "robotic scrub nurse" (Fischer, 2024); AI reduces infections, pain, and complications (Van der Meijden et al., 2023)	Early-stage; conceptual
OR practice	Central command suite; multimodal sensing; real-time decision support	CCS proposed for model-guided surgery; smart OR platforms integrate multimodal data (Padmanabhan, 2017)	Early-stage; infrastructure-dependent
OMFS	Lesion classification; orthognathic planning; risk prediction	AI enhances diagnostic accuracy and surgical planning; most studies retrospective (Ahmed et al., 2021; Yan et al., 2021)	Moderate; validation gaps

Figure 1 presents a conceptual model of AI-enabled multidisciplinary surgical care, illustrating data flows and decision nodes across disciplines.

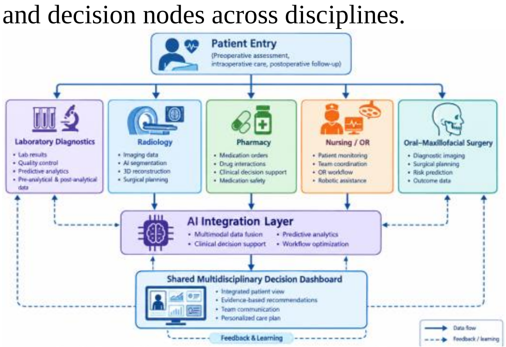

Figure 1. AI-Enabled Multidisciplinary Surgical Care: Conceptual Data Flow Model

4. Artificial Intelligence in Perioperative Pharmacy and Medication Safety

Perioperative medication management is a high-risk domain. Anesthesiologists working alone in the OR can diagnose, prescribe, prepare, administer, and monitor medications without the verification checks that are standard in other hospital settings (Paiste et al., 2024). Medication errors in this context are common, frequently preventable, and can cause significant physiological disturbance. AI and digital health technologies offer mechanisms to introduce redundancy and decision support without disrupting OR workflow.

Computerized physician order entry (CPOE) systems, electronic medication administration records, and barcode medication administration systems have been proven to reduce medication errors (Paiste et al., 2024). These technologies form the digital infrastructure upon which AI applications can be layered. AI-enhanced CDSS can integrate patient-specific factors—renal function, allergy history, current medications, surgical phase—to generate real-time dosing recommendations and contraindication alerts. Predictive models can identify patients at elevated risk for perioperative adverse drug events, enabling preemptive pharmacist review and modified anesthesia plans.

A systematic review and meta-analysis of CDSS in real-world perioperative care found that CDSS significantly reduced medication errors (OR 0.33; 95% CI, 0.30–0.36; $P < 0.00001$) (Cai et al., 2024). Studies evaluating anesthesiologist performance demonstrated that CDSS-assisted groups achieved significantly higher checklist performance scores compared to control groups (15.70 ± 1.93 vs. 12.95 ± 2.16, $P < 0.0001$). Additionally, anesthesiology trainees using CDSS scored $92.4 \pm 6.6\%$ on antithrombotic management questions versus $68.0 \pm 15.8\%$ in the control group ($P < 0.001$). These findings demonstrate that AI-enhanced decision support can meaningfully improve perioperative medication safety.

AI applications in pharmacy extend beyond error prevention. Machine learning models can predict individual patient responses to analgesic regimens, supporting personalized pain management. Models predicting postoperative nausea and vomiting risk can guide prophylactic antiemetic selection. Antibiotic stewardship algorithms can recommend surgical prophylaxis based on procedure type, patient allergy profile, and local resistance patterns. A pharmacist-led surgical medicines prescription optimization and prediction service incorporating a machine learning–based warning model has demonstrated improvements in medication safety and patient outcomes in a tertiary hospital setting (Hasan, 2024). This approach positions the pharmacist as a central node in the AI-enabled medication safety network, bridging laboratory data with surgical and anesthesia decision-making.

Barriers to pharmacy AI integration include workflow misalignment, alert fatigue, and lack of pharmacist involvement in AI design. CDSS that generate excessive non-specific alerts are ignored by clinicians, a phenomenon well documented in non-surgical settings and increasingly recognized in perioperative contexts. For pharmacy AI to enhance rather than disrupt surgical care, models must be calibrated to produce high-specificity alerts and integrated into existing medication reconciliation workflows.

5. Artificial Intelligence in Nursing and Operating Room Practice

The OR is a dynamic, high-stakes environment where surgeons, nurses, anesthesia providers, and technicians must coordinate under time pressure. Nursing roles in this environment—circulating nurse, scrub nurse and post-anesthesia care nurse—involve continuous monitoring, anticipatory preparation, and communication that are essential to patient safety. AI is beginning to augment these functions, though the evidence base remains less developed than in radiology or laboratory medicine.

Bibliometric analysis reveals a convergence toward AI-driven perioperative nursing practice, with emerging clusters around "robotic scrub nurse," "natural language processing," and "intelligent operating room nursing" (Fischer, 2024). Robotic scrub nurse concepts aim to automate instrument handling and count verification, reducing cognitive load on nursing staff and freeing them for higher-level monitoring and communication tasks. While fully autonomous robotic scrub nurses remain investigational, semi-automated systems for instrument tracking and sponge counting have demonstrated feasibility.

AI coaching systems represent a different modality of nursing and OR support. An AI Coach for enhancing teamwork in the cardiac OR has been developed using multimodal sensor data and explainable AI algorithms to generate interpretable feedback on team coordination (Dias, 2022). The system monitors communication patterns, role clarity, and situational awareness, providing real-time or near-real-time feedback that can improve team performance. This application treats AI not as a replacement for human team members but as a facilitator of human collaboration—a framing that aligns with nursing's relational and communicative foundations.

Intelligent monitoring in the OR encompasses vital sign analysis, depth-of-anesthesia assessment, and early warning systems for physiological deterioration. Machine learning models analyzing continuous physiological data streams can detect subtle trends that precede adverse events, providing nurses and anesthesiologists with lead time for intervention. Smart operating room platforms integrate physiological monitoring, medical imaging, instrument motion data, surgical video, and environmental metrics into centralized interfaces, enabling synchronized documentation, workflow coordination, and team communication (Thacharodi et al., 2024).

Postoperative nursing care is similarly amenable to AI augmentation. Machine learning models predict postoperative complications—surgical site infection, delirium, unplanned ICU admission—from electronic health record data, enabling risk-stratified nursing surveillance (Brydges et al., 2024; Hassan et al., 2023). An integrative review of AI in perioperative nursing found that AI contributed to clinical risk management, acting as a protective factor against complications and adverse events by enabling predictive analysis of clinical data, continuous monitoring, and decision support (Van der Meijden et al., 2023). Studies included in this review found that AI applications in colon surgery, hysterectomies, and cerebral aneurysm surgery contributed to reductions in infections, pain, intraoperative bleeding, and postoperative complications, with significant effects on surgical time, length of hospital stay, and hospital costs.

However, nursing AI faces distinctive challenges. The nursing workforce is heterogeneous in digital literacy, and AI tools must be designed for usability across this spectrum. Ethical concerns about surveillance and dehumanization of care are particularly salient in nursing contexts. Furthermore, nursing data—often unstructured, narrative, and context-rich—is challenging to standardize for machine learning. Inclusive design processes that center nurses as co-creators, not merely end-users, are essential for successful integration. AI in nursing represents an important advance for continuity of care by promoting greater efficiency, diagnostic accuracy, and personalized therapeutic planning, acting as a support to nurses in monitoring patients and analyzing clinical data (Van der Meijden et al., 2023).

6. Artificial Intelligence in Operating Room Practice and Multidisciplinary Integration

Beyond nursing, the OR as a whole is becoming a site of AI-enabled infrastructure. The concept of the "central command suite" (CCS) has been proposed as a futureproofing architecture for next-generation surgical environments (Padmanabhan, 2017). The CCS functions as a central information hub, interconnected with OR theaters, imaging facilities, and perioperative data systems. Its objective is to facilitate direct, in-person connections between surgeons, interventionalists, radiologists, and other clinicians, amplifying communication and coordinating key decisions. The CCS covers time scales ranging from preoperative planning to postoperative observation, and from a single intervention to the orchestration of an entire OR suite (Adewusi et al., 2023). The space is designed to plan surgical workflows and control their execution using model-guided medicine (MGM), serving as the central control hub to organize and optimize perioperative data.

This architectural vision addresses a critical gap in current AI implementation: the absence of a unified platform through which discipline-specific AI outputs can be synthesized. Laboratory AI, radiological AI, pharmacy AI, and nursing AI currently operate in isolation, each generating predictions that may not reach the decision-makers who need them. The CCS provides the physical and informational infrastructure for multidisciplinary AI integration, enabling MGM in which AI-derived insights are deliberated by the full surgical team.

Multimodal sensing represents another frontier in OR AI. Systems that integrate video, audio, physiological data and instrument tracking can generate a holistic representation of surgical activity. Computer vision and AI tools are being applied to surgical video and kinematic data to identify procedural phases, assess performance, and recognize critical events (Thacharodi et al., 2024). Smart operating room platforms integrate these multimodal data sources into centralized interfaces, enabling synchronized documentation, workflow coordination, and team communication. Machine learning models trained on these multimodal datasets can predict operative duration, identify deviations from planned workflow, and flag safety-critical events.

Real-time AI decision support in the OR faces stringent latency requirements. Models must generate predictions within the temporal constraints of surgical decision-making—often seconds to minutes, not hours. This necessitates edge computing architectures and optimized model inference. Data challenges are also pronounced: one minute of surgical video is estimated to contain 25 times the data volume of a CT scan (Etienne et al., 2020). Annotating this data requires expert surgeons, creating a bottleneck in model development. Furthermore, AI-driven approaches to managing surgeon fatigue and improving performance represent an emerging application area, with potential to optimize scheduling and intraoperative workload distribution (Rafaih & Ari, 2024). Table 2 outlines the key integration challenges and proposed solutions across the multidisciplinary AI landscape.

Table 2. Integration Challenges and Proposed Solutions for AI-Enabled Multidisciplinary Surgical Care

Challenge	Manifestation Across Disciplines	Proposed Solution
Data heterogeneity and standardization	Inconsistent annotation, variable protocols, single-center datasets	Standardized data-sharing frameworks; multi-institutional consortia (Ahmad et al., 2020)
Algorithmic opacity	Clinician distrust; difficulty interpreting model outputs	Explainable AI methods; feature attribution; similkty classification (Zhang et al., 2022)
Real-time processing constraints	Latency requirements in OR; data volume from video and sensors	Edge computing; optimized inference architectures (Hussain et al., 2022)
Workflow misalignment	AI tools not integrated into clinical pathways; alert fatigue	Human-centered design; pharmacist, nurse, and surgeon co-creation (Paiste et al., 2024)

Regulatory and liability uncertainty	Unclear responsibility for AI-supported decisions	Adaptive regulatory frameworks; clinician-in-the-loop models (Etienne et al., 2020)
Interoperability gaps	Laboratory, radiology, pharmacy, and OR systems siloed	Central command suite architectures; FHIR-based data exchange (Adewusi et al., 2023)

Figure 2 illustrates the temporal integration of AI across the surgical patient journey.

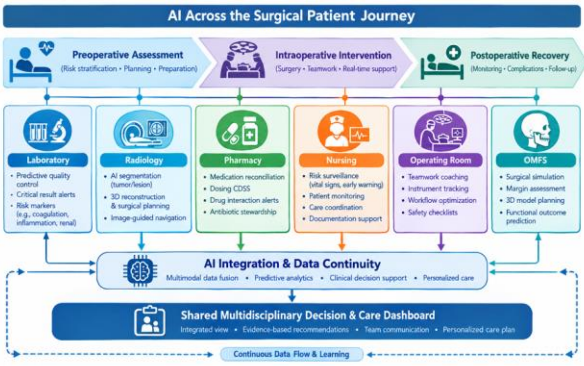

Figure 2. Temporal Integration of AI across the Surgical Patient Journey

[Insert Figure 2: A timeline from preoperative assessment through intraoperative intervention to postoperative recovery, with AI applications mapped to each phase: Laboratory (predictive QC, risk markers), Radiology (segmentation, 3D planning), Pharmacy (medication reconciliation, dosing CDSS), Nursing (risk surveillance, monitoring), OR (teamwork coaching, instrument tracking), OMFS (surgical simulation, margin assessment). Arrows indicate data continuity across phases.]

7. Artificial Intelligence in Oral and Maxillofacial Surgery: A Microcosm of Multidisciplinary Integration

OMFS exemplifies the multidisciplinary character of surgical care. The specialty integrates radiological imaging, clinical examination, histopathological interpretation, laboratory data, and multidisciplinary decision-making (Hung et al., 2023). Clinicians routinely evaluate panoramic radiographs, CBCT, CT, MRI, intraoral findings, functional assessments, and patient-specific anatomical and systemic factors. Many OMFS decisions rely on subtle imaging patterns, borderline diagnostic categories, and risk estimations that are inherently uncertain. As a result, interobserver and intraobserver variability remains a persistent challenge.

AI applications in OMFS span the full surgical pathway. In diagnosis, deep learning models classify odontogenic cysts and tumors from panoramic radiographs with accuracy comparable to oral radiologists. Convolutional neural networks detect and classify jaw lesions, potentially enabling earlier detection in primary care settings. In orthognathic surgery, automated landmark detection and surgical simulation support virtual treatment planning, reducing planning time and improving accuracy. A scoping review of AI in orthognathic surgery identified two primary application categories: diagnosis and treatment planning, with AI used for osteotomy design and bony reference point determination with accuracy ranges of 3.99–4.73 mm (Mohaideen et al., 2022). AI-based predictive models guide treatment strategy selection by analyzing medical history, imaging data, and surgical records to assess prognosis and postoperative complication risk (Hung et al., 2023).

Implantology benefits from AI-enhanced CBCT analysis. Automated bone density assessment and implant site evaluation support preoperative planning. Machine learning models predict implant success based on anatomical and patient factors. In oral oncology, AI supports tumor segmentation, margin assessment, and prognostic modeling. AI-assisted stimulated Raman molecular cytology has demonstrated accuracy in intraoperative surgical margin assessment, potentially reducing positive margin rates. A comprehensive analysis of published works confirms that current AI and ML applications in maxillofacial surgery are focused mainly on evaluating digital diagnostic methods, especially radiology, with particular emphasis on implant planning and lesion classification (Motie et al., 2023).

Risk prediction is a particularly active area. AI models predict inferior alveolar nerve injury in impacted third molar surgery, surgical difficulty, and postoperative complications. These predictions enable risk-stratified surgical planning and informed consent. The OMFS literature, however, reveals a consistent limitation: most studies are retrospective, single-center, and lack external validation (Dong et al., 2024; Czako et al., 2024). Methodological heterogeneity and inconsistent outcome definitions impede meta-analysis and translation. The gap between promising research results and routine clinical implementation remains wide.

OMFS AI research also highlights the importance of multidisciplinary data integration. Predictive models that incorporate laboratory data (inflammatory markers, nutritional status), pharmacy data (anticoagulation, bisphosphonate history), and nursing data (comorbidity burden, functional status) alongside imaging are likely to outperform imaging-only models (Pereira, 2021). Yet such multimodal models are rare. The specialty thus serves as both a test case and a cautionary tale for AI-enabled multidisciplinary surgical care: the clinical need is evident, the data exists, but the integration infrastructure and validation frameworks lag behind technical capability. AI can enhance the precision and efficiency of diagnostics and treatments in OMFS, with demonstrated capacity to improve clinical workflows and patient outcomes (Rasteau et al., 2022).

8. Challenges, Ethics, and Implementation Barriers

The translation of AI from research to routine multidisciplinary surgical care faces interconnected barriers spanning data, technology, ethics, and organization. Data challenges are foundational. AI models require large, well-annotated, diverse datasets. In surgery, data generation is abundant but annotation is labor-intensive and requires expert clinicians. Variability in surgical techniques, patient anatomy, and data collection methods across institutions creates heterogeneity that undermines model generalizability (Mithany et al., 2023). Reluctance to share surgical data—driven by privacy concerns and legal uncertainty—limits the scale of training datasets. A systematic review found that only 45% of surgical AI models present high-quality validation, and only 14% share datasets publicly, creating a substantial reproducibility and generalizability gap (Zhang et al., 2022).

Real-time application constraints are particularly acute in the OR. Models that generate predictions hours after data acquisition are of limited use during surgery. Latency requirements demand edge computing and optimized inference architectures. Data volume—especially from surgical video—creates storage and processing challenges. The gap between research-grade AI and real-time clinical AI is substantial (Ahmad et al., 2023).

Ethical considerations include algorithmic bias, transparency, accountability, and patient privacy. AI models trained on non-representative datasets may perform poorly for underrepresented populations, exacerbating health disparities. The "black box" problem—where model decision-making is opaque—undermines clinician trust and informed consent (Adegbesan et al., 2024). Responsibility for AI-supported decisions remains legally ambiguous: when an AI-generated prediction contributes to patient harm, liability allocation between clinician, institution, and developer is unclear (Cunha Reis, 2024). Data privacy concerns are heightened in surgical contexts where video and imaging data are inherently identifiable. Surgeons may also develop over-reliance on AI recommendations, risking diminished clinical skills and increased surgical errors if AI systems fail or provide erroneous guidance (Adegbesan et al., 2024).

Explainable AI (XAI) has emerged as a critical enabler of clinical trust. Surgeons are more likely to accept AI recommendations when the model's reasoning is interpretable (Zhang et al., 2022). XAI methods include global explanatory features, individual explanatory features, imaging-specific methods (saliency maps, class activation maps), time-series explanations, similarity classification, and rule extraction. However, recent studies have revealed shortcomings in achieving trust-related goals through XAI, questioning the widespread endorsement of XAI by medical professionals (Wabro & Herrmann, 2024). The time-sensitive nature of surgical environments frequently precludes adequate consideration of system explanations, meaning XAI-CDSS may not meet expectations of augmenting clinical decision-making in circumstances where time is of the essence. This suggests that XAI endorsement should be context-specific rather than universally mandated (Wabro & Herrmann, 2024). Furthermore, explainability and trustworthiness, while related, are distinct targets in clinical AI: explainability is a property of the system, while warranted trust depends on institutional capacity to act on what explanations reveal (Zhang et al., 2022).

Organizational barriers include workflow misalignment, lack of interoperability, and insufficient training (Bellini et al., 2021). AI tools designed without clinician input often fail in practice. Alert fatigue from over-sensitive CDSS erodes clinician engagement. Siloed information systems prevent data flow across laboratory, radiology, pharmacy, and OR domains. Clinicians also face cultural and time-related constraints, while researchers and industry stakeholders struggle with validation, return on investment, and deployment challenges; patients, meanwhile, worry about privacy and the loss of human touch (Byrd & Tignanelli, 2024). Central command suite architectures represent one response to this fragmentation, but their implementation requires substantial infrastructure investment and organizational change (Adewusi et al., 2023). Surgeon engagement helps bridge the gap between engineering and clinical utility, making AI tools more usable and clinically relevant.

9. Future Directions and Research Priorities

Four priorities emerge for advancing AI-enabled multidisciplinary surgical care. First, multimodal foundation models should be developed and validated. Current AI applications are predominantly unimodal—imaging AI, laboratory AI, pharmacy AI operating in isolation. The clinical reality is multimodal: surgical decisions integrate laboratory results, imaging findings, medication history, nursing assessment, and patient preferences. Foundation model architectures capable of integrating these heterogeneous data streams are maturing and hold potential for more clinically meaningful predictions (Varghese et al., 2024). Deep learning and multimodal neural networks have shown particular promise in orthopedic surgery, where imaging datasets are integrated with clinical data to enhance diagnostic and prognostic accuracy (Bozzo et al., 2024).

Second, prospective, multicenter validation must replace the current reliance on retrospective, single-center studies. The OMFS literature illustrates this gap: promising accuracy metrics from retrospective datasets have not translated into routine clinical use (Dong et al., 2024). Prospective validation with clinically meaningful endpoints—not just statistical accuracy—is essential. Moving forward, it is imperative to collect more expansive datasets to ensure procedural safety and generalizability of AI-assisted surgical techniques (Zeng et al., 2024).

Third, human-centered design and implementation science should guide AI development. Clinicians must be co-creators, not passive recipients. Implementation frameworks that address workflow integration, training, and change management are as important as algorithmic performance. The pharmacist-led SMPOP service demonstrates the value of embedding AI within existing professional roles and workflows (Hasan, 2024). Similarly, AI-driven approaches to managing surgeon fatigue and optimizing performance represent an emerging application area that requires careful human-factors engineering (Rafaih & Ari, 2024).

Fourth, regulatory and ethical frameworks must evolve to accommodate AI in surgical care. Adaptive regulation that balances innovation with patient protection, clear liability pathways, and mechanisms for post-market surveillance are needed. Professional societies should develop guidelines for AI-assisted surgical decision-making that preserve clinician judgment and patient autonomy. The integration of AI across the perioperative continuum—from preoperative risk assessment through intraoperative decision support to postoperative monitoring—creates a data cycle with the potential to enhance each phase of care, but this potential can only be realized within governance structures that prioritize patient safety and clinical accountability (Varghese et al., 2024; Quero et al., 2022).

10. Conclusion

AI is not a single technology but a set of computational methods that can be applied across the multidisciplinary landscape of surgical care. In laboratory diagnostics, it enhances quality, speed, and interpretive depth. In radiology, it improves planning precision and simulation fidelity. In pharmacy, it introduces safety redundancy into high-risk medication processes. In nursing and OR practice, it supports monitoring, teamwork, and workflow optimization. In OMFS, it spans the full surgical pathway from diagnosis to margin assessment. The integration of these applications into a coherent, multidisciplinary system requires more than technical performance. It requires interoperability, explainability, workflow alignment, ethical governance, and a deliberate architectural vision—such as the central command suite—that positions AI as a connective layer rather than a set of disconnected tools. The evidence reviewed here suggests that AI can enhance surgical care across disciplines, but only when implemented as a complement to, not a replacement for, multidisciplinary clinical expertise. The next decade of research should focus on prospective validation, human-centered design, and the organizational conditions that enable AI to fulfill its integrative promise. As Varghese et al. (2024) argue, the future of surgical AI lies not in autonomous systems but in augmented intelligence—where human judgment and machine computation converge to improve patient outcomes across the surgical continuum.

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