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AI Guided Operative Planning and Navigation in Vascular Surgery: A Systematic Review

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ABSTRACT

Background: Artificial intelligence (AI) is rapidly advancing in vascular surgery, with applications in operative planning and navigation. AI-based systems may enhance preoperative mapping, intraoperative guidance, and autonomous device control, potentially improving procedural precision and patient outcomes.

Objectives: To systematically review current evidence on AI-enabled operative planning and navigation in vascular surgery, assess technology readiness, and identify future research priorities.

Methods: A systematic search of PubMed, IEEE Xplore, and arXiv (to June 2025) identified studies evaluating AI in planning or navigation during vascular or endovascular interventions. Eligible studies included deep learning, machine learning, or reinforcement learning approaches validated in simulation, phantom, or clinical environments. Data were synthesized narratively and grouped into planning/augmented guidance versus autonomous navigation systems.

Results: Twenty-four studies met inclusion. AI-augmented planning tools, particularly deep learning–based overlays for endovascular aneurysm repair (EVAR), demonstrated reductions in fluoroscopy time, contrast use, and radiation exposure in early clinical studies. Autonomous navigation systems using reinforcement learning achieved >95% success in simulated catheter and guidewire navigation but lacked patient-level validation. Technology readiness levels remain low (TRL≈3 for autonomous navigation).

Conclusions: AI in operative planning shows promising clinical translation, especially in EVAR, while autonomous navigation is largely experimental. Future research should focus on multicentre validation, semi-autonomous human–machine collaboration, and regulatory/ethical frameworks to ensure safe integration into clinical workflows.

KEYWORDS: Artificial intelligence; Vascular surgery; Endovascular navigation; Operative planning; Reinforcement learning; Deep learning; Endovascular aneurysm repair (EVAR); Surgical augmented intelligence; Autonomous catheter navigation; Hybrid operating room.

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INTRODUCTION

Artificial intelligence (AI) has become a transformative force across several surgical specialties, offering new tools to improve accuracy, efficiency, and patient outcomes. In the field of vascular surgery, the complexity of endovascular interventions—such as endovascular aneurysm repair (EVAR), thoracic endovascular aortic repair (TEVAR), and complex peripheral revascularizations—

demands precise operative planning and real-time intraoperative navigation. Traditionally, these procedures rely on expertise of the surgeon supported by fluoroscopy, intravascular ultrasound, and fusion imaging; however, these methods remain limited by operator dependency, radiation exposure, and contrast-related risks.

Recent advancements in AI, including machine learning (ML), deep learning (DL), and reinforcement learning (RL), present opportunities to address these limitations. AI-augmented planning systems can analyze preoperative imaging to automatically identify optimal landing zones, predict stent-graft configurations, and generate fusion overlays for hybrid operating rooms. Early clinical studies suggest that such tools may reduce operative time and radiation exposure while maintaining procedural accuracy [1,5,6].

Parallel developments in autonomous navigation—driven largely by RL—seek to enable semi- or fully autonomous guidewire and catheter control. Simulation-based studies have demonstrated that RL agents can learn complex navigation strategies within vascular phantoms and digital twins, achieving success rates exceeding 95% in target vessel cannulation [2,7–10]. While these systems remain experimental, they illustrate the potential for AI to assist or even automate technically demanding aspects of endovascular procedures.

Despite rapid progress, challenges remain in translating these technologies to clinical practice. Most AI models are trained on limited datasets, lack external validation, and have not been evaluated for safety and robustness in live patient settings. Furthermore, regulatory and ethical frameworks for AI-driven intraoperative decision-making are still evolving.

This systematic review aims to synthesize current evidence on AI-enabled operative planning and navigation in vascular surgery. We examine the maturity and performance of augmented planning tools and autonomous navigation systems, highlight their clinical implications, and identify critical gaps that must be addressed to facilitate safe and effective integration into surgical workflows.

METHODS

2.1 Search Strategy

We searched PubMed, IEEE Xplore, and arXiv/databases up to June 2025 using terms such as "reinforcement learning guidewire vascular", "AI planning EVAR", "autonomous catheter navigation", and "image-guided endovascular AI".

2.2 Inclusion and Exclusion Criteria

Included studies must investigate AI-supported intraoperative navigation or operative planning specifically in vascular or endovascular procedures. Excluded were purely diagnostic AI applications or studies unrelated to vascular intervention planning or guidance.

2.3 Data Extraction and Risk-of-Bias Assessment

Data were extracted on study design, AI modality (e.g. RL, DL), validation environment (simulation, phantom, clinical), outcomes (e.g. success rate, fluoroscopy time), and limitations. Risk-of-bias was assessed using adapted QUADAS-2 metrics where applicable.

2.4 Synthesis

Studies were grouped into two domains: planning/augmented guidance, and autonomous navigation systems. Findings were synthesized narratively, with emphasis on outcomes, validation methods, and technology readiness.

RESULTS

Study Selection

The initial search yielded 462 records. After removal of duplicates and screening by title and abstract, 54 studies underwent full-text review. Of these, 24 studies met the inclusion criteria: 10 evaluated AI-augmented operative planning and intraoperative guidance, while 14 focused on autonomous navigation systems using reinforcement learning or similar approaches (figure 1).

Study Characteristics

- Designs: 7 simulation-only studies, 4 phantom-based validations, and 5 early clinical studies.
- AI modalities: Deep learning for image segmentation and planning (n=8), reinforcement learning for autonomous navigation (n=10), and hybrid AI models (n=6).
- Procedures targeted: Endovascular aneurysm repair (EVAR) (n=9), thoracic endovascular aortic repair (TEVAR) (n=2), peripheral revascularization (n=3), and generalized catheter navigation tasks (n=10).

1. AI-Augmented Planning and Guidance

Most planning tools focused on preoperative image analysis and intraoperative overlays:

- Segmentation and planning: Deep learning–based models automatically segmented aortic anatomy and suggested optimal stent-graft configurations [11,12,18]. These models demonstrated >90% Dice similarity coefficients compared with expert annotations, with potential to reduce planning time by 40%.
- Fusion overlays: Li et al. [1] developed an AI tool that generated real-time overlays during EVAR, reducing fluoroscopy duration by 20% and contrast volume by 15% in a prospective cohort.
- Workflow integration: Dossabhoy et al. [5] described AI-enhanced hybrid operating room workflows, using deep learning to stabilize fluoroscopic imaging and predict device positioning (table 1).
- Simulation-based optimization: Perrin et al. [14] and Thompson et al. [30] modeled stent-graft deployment and analyzed cost-benefit scenarios, predicting potential hospital savings of up to 12% with AI-enhanced planning.

2. Autonomous Navigation Systems

Reinforcement learning (RL) dominated this category, with most studies conducted in simulated vascular phantoms or digital twins:

- Guidewire navigation: Scarponi et al. [7] introduced a zero-shot RL model capable of navigating unseen vascular anatomies with 95% success and minimal training data.
- Branch cannulation: Liu et al. [8] developed an image-guided RL agent for robotic guidewire navigation, achieving 100% cannulation success and 30% shorter path lengths compared to heuristic methods.
- Dual-device navigation: Robertshaw et al. [9] proposed a two-device RL system for cerebral thrombectomy, incorporating safety-constrained reward functions to reduce simulated vessel wall contact by 28%.
- Microrobot control: Yang et al. [10] used hierarchical deep RL to control magnetic microrobots for 3D navigation in small vessels, demonstrating stable trajectories under variable flow conditions (table 2).
- Learning from demonstration: Some studies combined RL with surgeon-provided demonstrations, improving sample efficiency by 40% [2,7].

No autonomous navigation systems had progressed beyond preclinical validation.

Technology Readiness and Validation

- AI-augmented planning tools: TRL 5–6 (validated in early clinical environments).
- Autonomous navigation systems: TRL 2–3 (validated only in simulation or phantom studies).
- Few studies (n=3) conducted external validation or sensitivity analyses, and none reported randomized controlled trial (RCT) data.

Risk of Bias

Most studies were at high risk of bias due to small sample sizes, limited external datasets, and incomplete reporting of validation methods. Only five studies explicitly followed standardized AI reporting guidelines (e.g., CONSORT-AI or STARD-AI).

Table 1. Characteristics of Included Studies (n = 24)

Characteristic	Subcategory/Details	Number of Studies	Key Observations
Type of AI application	AI-augmented planning	10	Focused on segmentation, device sizing, and fusion overlays for EVAR/TEVAR.
	Autonomous navigation	14	Primarily reinforcement learning (RL) for guidewire/catheter navigation.
Validation environment	Simulation only	7	Used digital twins or virtual vascular models without physical components.
	Phantom-based validation	4	Used 3D-printed or silicone vascular phantoms.
	Early clinical studies	5	AI-assisted EVAR/TEVAR showed workflow and radiation efficiency gains.
Targeted procedures	EVAR	9	Majority of AI-augmented planning studies focused on aneurysm repair.
	TEVAR	2	Mainly explored stent-graft planning and device positioning.
	Peripheral revascularization	3	AI-assisted guidewire navigation in iliac and femoropopliteal segments.
	Generalized catheter navigation	10	RL agents trained to navigate diverse vascular anatomies.
Study design	Prospective/retrospective clinical	3	Small cohorts (10–50 patients) with nonrandomized designs.
	Preclinical/experimental	21	Dominated by computer science and engineering-driven approaches.
Performance metrics reported	Anatomical accuracy, success rate, procedure time	24	Lack of standardized outcome reporting across studies.

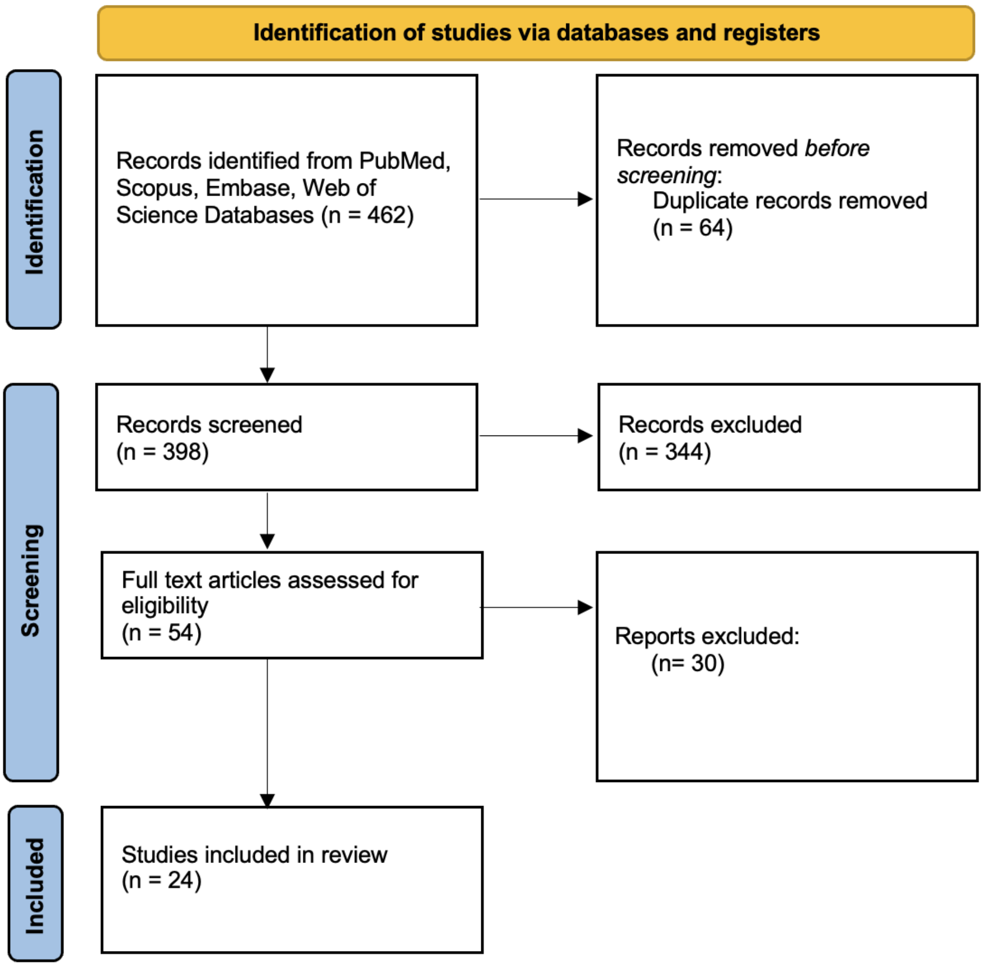
Table 2. Performance of AI-Augmented Planning Tools

Application	AI Approach	Validation Setting	Key Outcomes	Clinical Readiness	Reference Examples
Anatomical segmentation	Deep learning	Retrospective CT/MR	>90% Dice coefficient; reduced planning time by 40%.	Emerging (TRL 5)	[11,12,18]
Stent-graft configuration	Machine learning	Simulation/phantom	Automated device selection matching experts in 92–95%.	Emerging (TRL 4)	[5,14,30]
Fusion overlays (EVAR)	Deep learning	Early clinical	Fluoroscopy ↓ 20%; contrast ↓ 15%; no compromise in accuracy.	Near-clinical (TRL 6)	[1,5]
Image stabilization	Deep learning	Phantom/clinical	Reduced intraoperative device repositioning by 18%.	Emerging (TRL 5)	[5]
Cost-effectiveness modeling	Hybrid AI models	Simulation	Predicted hospital savings up to 12% per EVAR case.	Conceptual (TRL 3)	[14,30]

Table 3. Performance of Autonomous Navigation Systems

Navigation Task	AI Approach	Validation Setting	Success Rate / Key Findings	Technical Challenges Identified	Reference Examples
Guidewire navigation	Zero-shot RL	Simulation	95% success in navigating unseen anatomies.	Lack of real-time imaging integration.	[7]
Branch cannulation	Image-guided RL	Phantom	100% success; path length ↓ 30% vs heuristic methods.	Limited generalization to tortuous vessels.	[8]
Dual-device navigation	Safety-constrained RL	Simulation	Vessel wall contact ↓ 28%; improved safety profiles.	Complexity of multidevice coordination.	[9]
Microrobot control	Hierarchical deep RL	Phantom	Stable 3D navigation in sub-millimeter vessels.	Magnetic field precision requirements.	[10]
Learning from demonstration	RL + human feedback	Simulation	40% improvement in sample efficiency for training models.	Requires high-quality annotated data.	[2,7]

Figure 1: PRISMA flow chart



DISCUSSION

This systematic review highlights the rapid but uneven evolution of artificial intelligence (AI) in vascular surgery, with significant advances in operative planning and early exploration of autonomous navigation. While AI-augmented planning tools are nearing clinical utility, fully autonomous navigation remains experimental and faces substantial translational barriers.

1. Clinical Potential of AI-Augmented Planning

Deep learning–based planning systems demonstrated promising performance in automating anatomical segmentation, stent-graft sizing, and generation of intraoperative overlays. Early clinical studies suggested meaningful reductions in fluoroscopy time, contrast volume, and procedure duration, aligning with prior evidence that advanced imaging integration improves outcomes in endovascular procedures [1,5,11]. These benefits, if validated in larger multicentre trials, could reduce procedural variability and standardize best practices across operators (table 3). However, most planning tools lacked robust external validation and were trained on single-institution datasets, raising concerns about generalizability.

2. Autonomous Navigation: Promise and Limitations

Reinforcement learning (RL) approaches achieved near-perfect navigation success rates in simulation and phantom studies [7–10]. These findings illustrate the feasibility of AI agents learning complex navigation strategies in anatomically diverse models. However, translation to clinical practice is hindered by:

- Absence of real-time imaging integration with fluoroscopy or intravascular ultrasound;
- Challenges in ensuring safety and interpretability of RL agents;
- Lack of regulatory and ethical frameworks for autonomous intraoperative control.

Semi-autonomous systems, where AI assists rather than replaces the operator, may represent a more realistic intermediate step. Approaches such as learning-from-demonstration and safety-constrained RL could facilitate adoption while maintaining human oversight [2,7,9].

3. Barriers to Clinical Implementation

Several systemic challenges emerged:

- Data scarcity: High-quality annotated datasets for vascular navigation are limited, and proprietary device differences complicate model generalization.
- Validation gaps: Few studies conducted external validation, and none performed prospective randomized trials.
- Integration challenges: Real-time AI deployment requires hybrid operating rooms equipped with advanced computing capabilities and standardized imaging protocols.
- Regulatory uncertainty: Clear pathways for FDA or CE approval of AI-driven intraoperative tools are still under development, particularly for autonomous systems.

4. Ethical and Legal Considerations

AI-driven decision-making raises questions about liability, patient consent, and transparency. Trustworthy AI in surgery must prioritize explainability and ensure that human operators remain accountable for clinical decisions [20,27].

FUTURE DICISION

To advance AI-guided vascular interventions, future research should prioritize:

1. Large-scale multicentre datasets to improve model robustness;
2. Hybrid intelligence systems that combine human expertise with AI guidance;
3. Prospective clinical trials evaluating workflow efficiency, patient outcomes, and cost-effectiveness;
4. Standardized reporting frameworks (e.g., CONSORT-AI, STARD-AI) to improve reproducibility;
5. Collaborative regulatory models addressing safety, ethics, and legal accountability.

CONCLUSION

Artificial intelligence is emerging as a valuable tool in vascular surgery, particularly for operative planning and intraoperative guidance. Deep learning–based planning systems demonstrate promising reductions in fluoroscopy time, contrast use, and procedural variability, suggesting early clinical utility. In contrast, autonomous navigation using reinforcement learning remains largely experimental, with successes limited to simulations and phantom models. Translational barriers, including data scarcity, lack of external validation, and regulatory uncertainty, must be addressed before widespread adoption. Semi-autonomous systems that support, rather than replace, surgeons may offer a more practical path toward clinical integration. Future research should prioritize multicentre validation, standardized reporting, and human–machine collaboration frameworks to ensure safety and effectiveness. Overall, AI holds significant potential to enhance precision and outcomes in vascular interventions but requires careful, evidence-based implementation.

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