VER
Vascular & Endovascular Review

AI-Driven Image Segmentation for Preoperative Planning in Endovascular Aneurysm Repair (EVAR)

Mohammed Eltahir Abdelhag[1], Husham E. Homeida[2], Nahid Mahmoud Hassan Elamin[3], Badreldin S. R[4], Hind Ali Osman[5], Abuzer Abdalla[6]

[1]Department of Computer Science, College of Engineering and Computer Science, Jazan University, Saudi Arabia. mabdelhag@jazanu.edu.sa, mohedtahir@gmail.com
[2]College of Dentistry Department of Maxillofacial Surgery and Diagnostic Science, Jazan University, Saudi Arabia. hisham792@hotmail.com
[3]Department of Maxillofacial Surgery and Diagnostic Sciences, College of Dentistry, Jazan University, Saudi Arabia. nelamin@jazanu.edu.sa
[4]Department of Medical Laboratory Technology, College of Nursing and Allied Health Sciences, Jazan University, Saudi Arabia. brahama@jazanu.edu.sa
[5]Department of Preventive Dental science, College of Dentistry, Jazan University, Saudi Arabia. haosman@jazanu.edu.sa
[6]Department of Anatomy, Faculty of Medicine, Jazan University, Saudi Arabia. aaddalla@jazanu.edu.sa

ABSTRACT

Endovascular aneurysm repair (EVAR) relies on the accuracy of the preoperative assessment of the cases of abdominal aortic aneurysms (AAA), and the choice of the device and the procedure strategy depend on the quality of measurements of the anatomy. Traditional segmentation of computed tomography angiography (CTA) or magnetic resonance angiography (MRA) images can be tedious and operator-biased, and can create variability that can influence clinical outcomes. This paper presents a proposed AI-based image segmentation system to automate the process of aortic lumen, thrombus, and other morphological characteristics identification and description necessary during EVAR planning. Training The system is trained on manually annotated deep learning architecture projects on standardized ground-truth labeling vascular imaging datasets including variants of U-net and transformer-based segmentation. The workflow extends to include powerful preprocessing, automatic segmentation and extraction of clinically significant parameters including maximal diameter, neck length and vessel angulation. These deliverables are to be compatible with the already available EVAR planning tools. The framework shows the possibility of decreasing planning time, increasing reproducibility, and decision-making accuracy in contrast to the traditional manual or semi-automated workflows. The initial feedback of radiologists and vascular surgeons suggests that the AI-generated segmentations are very much in line with what is expected of a clinician, and the results are reliable across a range of imaging conditions. Also, the proposed system is designed as a modular construct, which allows its extension to other vascular bed territories, real-time intraoperative guidance and integration into 3D printing or virtual simulation tools. The methodology should help to boost clinical uptake and by enhancing explainability and interpretability to make clinicians more trusting.

KEYWORDS: AI segmentation, EVAR planning, abdominal aortic aneurysm, deep learning, medical imaging.

How to Cite: Mohammed Eltahir Abdelhag, Husham E. Homeida, Nahid Mahmoud Hassan Elamin, Badreldin S. R, Hind Ali Osman, Abuzer Abdalla., (2025) AI-Driven Image Segmentation for Preoperative Planning in Endovascular Aneurysm Repair (EVAR), Vascular and Endovascular Review, Vol.8, No.13s, 290-301.

INTRODUCTION

A. Background on abdominal aortic aneurysms (AAA) and EVAR

Abdominal aortic aneurysms (AAA) are a progressive vascular pathology that is characterized by permanent dilation of the abdominal aorta, which is usually determined by a diameter more than 1.5 times the normal vessel size. AAAs can be clinically silent, and rupture is a disastrous event, which is accompanied by the highest mortality rates. The population has grown older and imaging use has grown, with the resultant increase in incidence and detection of AAAs; thus, the need to diagnose and intervene promptly. The conventional forms of therapeutic interventions of the AAA are open surgical repair and endovascular aneurysm repair (EVAR). The reason why EVAR is the choice of most patients is its minimally invasive nature, lower rates of perioperative morbidity, and less time taken in recovery. The process entails the placement of a stent graft in the aneurysm sac, through transfemoral approach with an aim of isolating the weakened vessel wall to systemic pressure and thus rupture is prevented [1]. Nevertheless, EVAR requires clear anatomical knowledge since survival is highly dependent on a sufficient proximal and distal landing zones, vessel tortuosity, involvement of branches and thrombus burden. The imaging technique that is important in assessing these anatomical parameters is the high-resolution imaging, especially the computed tomography angiography (CTA). Radiologists and vascular surgeons should pay close attention to the interpretation of such images, which helps to define the use of EVAR, the choice of the equipment to be used, and predict complications during the procedure [2]. Even though EVAR has benefits, there are risks associated with EVAR, including endoleaks, device migration, and reintervention, which are usually associated with inaccuracies in measuring preoperative measurements. Consequently, enhancing the imaging interpretation and vessel segmentation is critical towards optimizing the results, as well as minimizing complications, and the long-term sustainability of the EVAR interventions.

B. Importance of Accurate Preoperative Planning

The key success factor of endovascular aneurysm repair (EVAR) is the proper planning prior to the operation since it directly affects the choice of the device, strategy, and long-term clinical outcomes. Since EVAR requires the establishment of a stable seal between the stent graft and normal sections of the vessels, there has to be accurate information of aortic morphology. Figure 1 demonstrates that proper planning makes EVAR safer with its help thanks to the effective assessment. The most important measurements, such as maximal aneurysm diameter, proximal neck length and angulation, iliac artery dimensions and thrombus distribution have to be obtained carefully on computed tomography angiography (CTA) or magnetic resonance angiography (MRA).

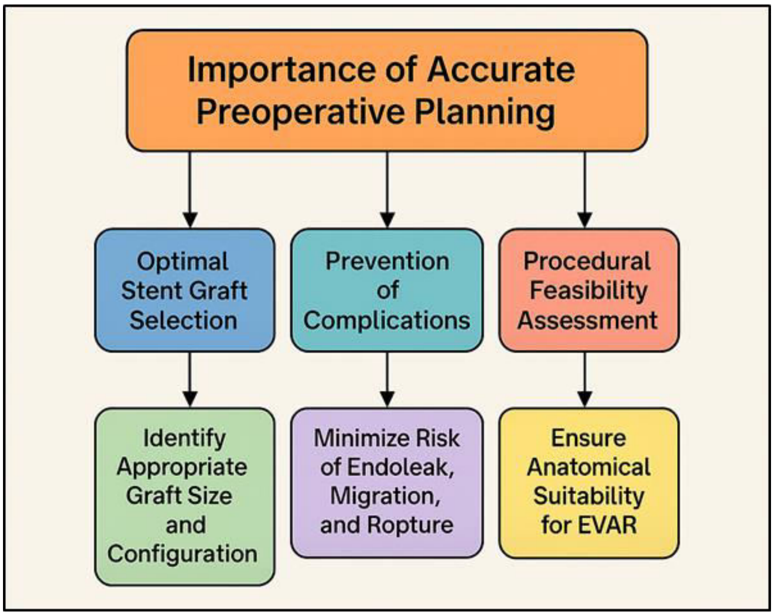

Figure 1: Flowchart of the Importance of Accurate Preoperative Planning in EVAR

Such errors can cause poor graft sizing which can cause complications like endoleaks, migration, occlusion of limbs, or secondary interventions. Preoperative planning is also useful in assisting clinicians to predict the challenges during the procedure, including tortuous iliac arteries or substantial calcification that would require adjunctive maneuvers [3]. In addition, proper anatomy description allows patient-specific procedural decision-making, such as the eligibility criteria to standard EVAR, fenestrated/branched devices, or alternative procedures. Segmentation and measurement activities are traditionally done by hand or using semi-automated systems, which are time-consuming and subject to interobserver variability, particularly in the case of an inexperienced operator. This is because the need to be more precise has increased due to more complex designs of the device and more heterogeneous patient anatomy. Thus, effective, efficient and consistent preoperative planning techniques are imperative in providing safe and effective treatment procedures. Enhancement of these workflows can greatly reduce planning period, confidence of the procedure, and eventually achieve long-term viability and overall success of EVAR [4].

C. Rationale for Integrating AI-Driven Segmentation

The application of AI-based image segmentation to the EVAR planning process can solve a number of old issues related to vascular imaging interpretation being done manually. The conventional segmentation techniques usually take a lot of specialization, time and physical effort and are prone to delays during planning and some disparities in the measurement accuracy. The models of deep learning-based vessel contouring segmentation, especially those based on the U-Net architecture and transformer-based designs, provide the capability of automating and standardizing vessel contouring at a high precision [5]. These models can quickly demarcate aortic lumen, mural thrombus, and other vascular structures based on large annotated datasets to find complex anatomical patterns and thus are able to delineate these structures even where imaging conditions can be challenging, such as heavy calcification or motion artifact. The automated method of segmentation reduces interobserver errors, as well as intraobserver errors, and yields more stable anatomical measurements that directly affect the size of the device and the strategy of the procedure [6]. Moreover, morphological features produced by AI, including diameters, neck aspects, and tortuosity indices, may be automatically incorporated into the EVAR planning software and allow more efficient workflows, as well as a decrease in the workload of clinicians. The growing accessibility of high-quality imaging data and the progress of computer resources through the use of GPUs also contribute to the viability of such models in a large scale [7].

LITERATURE REVIEW

A. Overview of EVAR workflow and imaging modalities (CTA, MRA)

The procedure of the endovascular aneurysm repair (EVAR) depends on a well-designed workflow, which is supported by proper diagnosis and proceeds to thorough preoperative planning, device selection, intraoperative implementation, and follow-up. The high-quality imaging of the vessels is the key to this workflow as it offers the anatomical detail needed to assess the morphology of an aneurysm and the possibility of the procedure. The most common modality is computed tomography angiography (CTA), as it has a high spatial resolution, is fast to acquire, and can be used in the 3D reconstruction software [8]. With the help of CTA, it is possible to visualize the aortic lumen, thrombus, calcifications, branch vessels, and access pathways with accuracy. Multiphase CTA also aids in the detection of endoleaks in follow up. Magnetic resonance angiography (MRA), which is not widely used in EVAR planning, has no radiation and high-quality soft-tissue contrast. It is also especially significant when the patients have contraindications to iodinated contrast or need to undergo more than one imaging. Non-contrast-enhanced angiography is one of the more advanced MRA methods that improve its use in high-risk groups [9]. The EVAR workflow is usually a process that involves segmentation of the aorta and iliac arteries, measurement of key parameters that include proximal length of the neck, angulation and aneurysm size, and evaluation of device appropriateness. To evaluate the integrity of the grafts and identify any complications like endoleaks, graft migration or expansion of the sacs, postoperative imaging is required. This complexity in patient anatomy and technology of the devices puts emphasis to the importance of the high precision of the imaging-based assessment [10]. In this way, the literature stresses the key role of imaging in assessing the achievement of EVAR and highlights the current developments in image acquisition, reconstruction, and analysis. The innovations offer an excellent platform to incorporate AI-based methods that fulfill the purpose of streamlining and improving the current processes.

B. Traditional Segmentation Techniques in Vascular Imaging

In EVAR planning, computational analysis in vascular imaging has been decades old based on the traditional segmentation methods. The methods are largely related to manual delineation or classical image processing algorithms and are designed to identify vascular structures, including the aortic lumen and thrombus on scans of either CTA or MRA. The manual segmentation technique, despite being very precise with a highly experienced user, is time-consuming, laborious and subject to interobserver variability, especially in difficult cases that are highly calcified or irregularly shaped thrombus [11, 12]. Semi-automated algorithms were developed as an attempt of minimizing the amount of work and preserving accuracy. These methods are normally based on thresholding, region growing, edge detection or deformable contour models like active contours (snakes) and level-set methods. Thresholds methods take advantage of the variations in the intensity of images of blood and thrombus and the surrounding tissues but fail to work well in areas where there is overlap of intensities. Regional growing techniques are able to enhance delineation, however, they frequently need user specified seeds and parameters. Edge-based methods rely on gradient data hence sensitive to noise and low contrast [13]. Deformable models also strive to deform a model contour to object edges based on a tradeoff between image-based forces and shape priors, provides greater robustness, but needs much initialisation and tuning. Although these classical techniques formed the foundation of quantitative vascular analysis, their weaknesses, especially in scaling, speed and consistency became more evident as increasingly large volumes of imaging were required and clinical requirements grew.

C. AI and Deep Learning Techniques for Medical Image Segmentation

Medical image segmentation This has transformed medical image segmentation because AI and deep learning have made it possible to automatically extract elaborate structures of the anatomy with greater accuracy and scalability than ever. Most segmentation models are based on convolutional neural networks (CNNs), and the U-Net architecture is a groundbreaking development because it has an encoder-decoder design and includes skip connections that maintain spatial detail [14]. Many versions of U-Net, such as attention U-Nets, residual U-Nets, and 3D U-Nets, have been shown to be effective on various vascular imaging tasks, with better lumen and thrombus delineation in a variety of patient anatomies. Even more recently, the use of transformer-based models, including Swin-UNet and TransUNet, has now extended the segmentation functionality of CNNs by modeling long-range spatial dependencies, which CNNs by definition cannot do [15]. These architectures have been found to be especially useful in large volumetric datasets, which are appealing to CTA-based EVAR planning. Deep learning models are based on big and annotated datasets and they can be trained with data augmentation, transfer learning and specialized loss functions that work with class imbalance. In addition to segmentation, AI-based pipelines are capable of extraction of morphological features, geometric measurements, and incorporating predictive analytics and provide a complete decision support [16]. According to the studies, AI models are always faster, reproducible, and more accurate than traditional segmentation models, with less reliance on the expertise of the operator. Table 1 provides an overview of the developments and trends that define AI-based vascular segmentation studies. Increasing clinical interest has led to research focusing on increasing model interpretability, multi-center dataset domain adaptation, and imaging artifact-resilient modeling.

Table 1: Summary of Related Work in AI-Driven Vascular Image Segmentation for EVAR

Method	Target Structure	Key Findings	Impact / Future Trend
Classical Level-Set Segmentation	Aortic Lumen	Improved lumen boundary detection	Shift toward automation to reduce manual corrections
3D U-Net [17]	AAA Segmentation	Strong volumetric performance	Adoption of 3D deep learning for complex vascular shapes
Active Contour Models	Lumen & Thrombus	Effective on smooth boundaries	Limited robustness → need for AI hybrid methods
Deep CNN (U-Net)	AAA Lumen	High Dice accuracy	More focus on thrombus segmentation accuracy
Residual U-Net	Lumen & Thrombus	Good generalization	Move toward multi-center training
Attention U-Net [18]	Aortic Neck	Improved boundary precision	Attention mechanisms widely adopted for EVAR
TransUNet	AAA & Iliac Arteries	Handles global context	Transformers emerging as new standard

Swin Transformer	Vessel Tree	Best performance on complex anatomy	Future: hierarchical transformers for EVAR
Hybrid CNN + Graph Models	Centerline Extraction	Accurate tortuosity mapping	Integration with automated graft planning
Multi-task CNN [19]	Lumen + Measurements	Simultaneous segmentation + measurement	Trend: end-to-end EVAR planning
Semi-supervised CNN [20]	Lumen & Thrombus	Reduced annotation requirements	Growth in weakly supervised EVAR segmentation
Ensemble Models	AAA Morphology	More stable performance	Ensemble approaches for clinical reliability
Diffusion-Based Models	Aortic Mask Generation	High-quality, smooth segmentation	Trend: generative AI for anatomical realism
U-Net + Transformer Hybrid [21]	Lumen, Thrombus, Neck	Fast, high-accuracy automated EVAR planning	Future: real-time OR integration + 3D printing

METHODOLOGY

A. Dataset acquisition and preprocessing

Training on an AI-based segmentation framework of EVAR planning needs a strictly filtered dataset, which includes anatomical variation and imaging variability in clinical practice. The acquisition of data in AAA evaluation generally starts with the acquisition of contrast-enhanced computed tomography angiography (CTA), which is the preferred modality of AAA examination based on its high spatial resolution and reproducible visualization of the lumen and thrombus of the aorta. The cases must capture a wide range of aneurysm morphology including differences in thrombus burden, calcification, aortic angulation and iliac artery anatomy in order to guarantee that the model can be generalized. Imaging parameters including slice thickness, contrast phase and reconstruction kernels are also vastly different among the scanners requiring standard preprocessing steps. Anonymization is used as a first step of preprocessing to ensure privacy of patients, and then the data is converted to standard formats, including NIfTI or DICOM series with uniform orientation. It is done by the application of intensity normalization to reduce scanner-specific variability, which is usually done by windowing based on Hounsfield units relevant to the vascular structures.

B. Annotation Standards and Ground Truth Generation

The ground truth annotation is a vital part of the development of credible AI models to aortic segmentation because the accuracy of the model is essentially the accuracy of the labeling. Annotation is normally done by skilled radiologists or vascular imaging experts who manually outline the lumen of the aorta, thrombus and in some cases, other neighboring arteries like the renal or iliac arteries. To ensure the minimum interobserver variability and consistency throughout the dataset, the standardized protocols of annotation are necessary. Such protocols typically specify anatomical limits, contouring guidelines on problematic areas, and treatment of unclear areas with calcification, motion artifact or low contrast. Figure 2 demonstrates uniform steps taking to account standardized steps, which guarantee the stability of annotation and valid ground truth. It is annotated with specialized medical imaging software that has the ability to label individually 2D and 3D which results in delineation at the voxel level. Multi-planar review is done to make sure that there are anatomically accurate contours between axial, coronal, and sagittal slices. To improve trustworthiness, a multi-step review procedure can be adopted: the primary annotator can be followed by a senior expert who will then review the annotations made by the former, and a consensus will be reached on the inconsistency. In other instances, consistency is validated by quantitative measures such as Dice scores in between annotators. After they are complete, annotations are transformed into segmentation masks in concordance with the respective volumes.

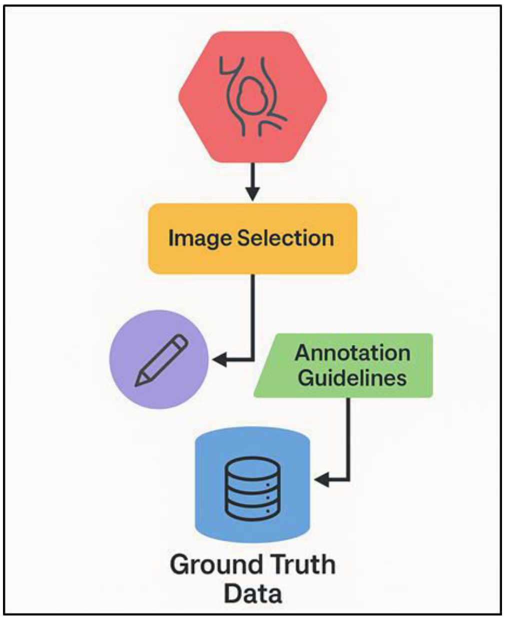

Figure 2: Process Diagram for Annotation Standards and Ground Truth Development

These masks are used as ground truth of supervised learning. Other derived annotations like centerlines, diameter measurements and vessel orientations can also be generated to facilitate morphological analysis later. The guarantee of quality ground truth datasets does not only enhance the overall performance of models, but also allows the fair assessment and comparison of the different architectures. The dataset is a powerful source of training clinically reliable segmentation models through stringent standards of annotation.

C. AI model architecture selection

1. U-Net variants

U-Net and its numerous variants are the basis of the modern medical image segmentation system because of their elegant encoder-decoder structure and capacity to maintain the spatial resolution by using skip connections. The baseline U-Net design posed a contracting pathway with semantic features, and an expanding pathway with fine spatial features, and is therefore effective at segmenting irregular-vascular boundaries. Over the years, many improvements have been suggested to make the performance on difficult datasets like CTA scan of abdominal aortic aneurysms better. Integrated U-Nets Residual U-Nets incorporate residual learning to enhance gradient flow and stabilization of training especially with large volume deep network training. Attention U-Nets include attention gates which emphasize on the relevant organs and enable the model to emphasize lumen-thrombus boundaries and ignore irrelevant background structures. Dense U-Nets provide dense connectivity to provide a feature reuse on the feature sharing and help in segmentation with the minimum extra computation cost. In the case of 3D vascular imaging, 3D U-Net versions generalize convolutional operations to the volumetric space and acquire inter-slice contextual detail that is important in the correct estimation of the morphology of an aneurysm.

2. Transformers

The use of transformer-based architectures has quickly become popular in medical image segmentation with their ability to represent long-range interactions and encode the global anatomy context features, which address the local feature extraction capabilities of convolutional networks. Transformers were initially designed to process natural language by utilizing self-attention networks that determine relationships between every sequence position. These mechanisms when applied to imaging tasks enable the model to evaluate spatial correlations between more distant regions enhancing segmentation performance through structures of non-simple geometry like the aorta and iliac arteries. Other models like TransUNet are transformer-based encoders with U-Net decoders, which make use of the global reasoning of the transformer and retain accurate boundary reconstruction. Swin Transformers add hierarchical attention windows which cut down the computational expense and to the high-resolution volumetric scans which are especially applicable to CTA-based EVAR planning. ViT derivatives can be applied to images in patches so that they can be processed in flexible and modular pipelines, which can be adjusted to various imaging dimensions. Transformers are very robust to changes in imaging quality, anatomical anomalousities and noise.

PROPOSED AI-DRIVEN SEGMENTATION FRAMEWORK

A. Workflow overview

The suggested AI-based segmentation framework will automatize and improve the preoperative planning procedure of EVAR by delivering complete computer-generated, correct, and repeatable anatomical results. The process starts with obtaining quality CTA scans which are preprocessed to assure some level of standardization in variations of the scanner setting, positioning of the patient and contrast enhancement. The subsequent morphological analysis is based on these masks. After segmentation, geometric algorithms and centerline-based measures identify clinically relevant parameters of diameters, neck structure, tortuosity and thrombus burden in the framework. These measurements would help to choose the right size of stent grafts and also define the possibility of EVAR. The framework then summarizes the segmented structures and the resulting measures into a comprehensible output that could directly be incorporated into the already existing EVAR planning software. The visualization elements enable the clinicians to view 2D cross-sections, 3D reconstructions and interactive models in order to confirm the AI generated outputs. Quality assurance is also a part of the workflow, such as confidence scoring and automatic anomaly flags, which notify clinicians about the areas in which the model is not so sure. The proposed workflow will greatly decrease the amount of time required to prepare a plan by automating labor-intensive parts of the process without sacrificing the interpretation or clinical oversight.

B. Automated Aortic Lumen and Thrombus Segmentation

The main aspect of the suggested framework is automated aortic lumen and mural thrombus segmentation that can be used to complete morphological characterization needed to plan the EVAR. The AI model takes pre processed CTA volumes and produces voxel based predictions that distinguish between lumen, thrombus and surrounding tissues. Deep learning networks, i.e., 3D U-Nets, attention-enhanced U-Nets or transformer models are trained on strictly annotated data to detect more complex patterns of the anatomy, i.e. thrombus shape variations, calcification extent, lumen discontinuities etc. The lumen segmentation step normally entails the emphasis of contrast enhanced blood pool, which enables the model to outline inner arterial boundary spatial with high resolution. Heterogeneity of thrombus density and overlap with other structures makes the segmentation of the thrombus more difficult. The attentional mechanisms, multi-scale feature extraction and higher quality loss functions like boundary-aware or focal Dice loss play a significant role in enhancing performance in such challenging areas. The result is two 3D masks of both structures, including anatomically consistent structures.

C. Extraction of Morphological Features (Diameters, Neck Length, Angulation)

After the lumen and thrombus segmentations are obtained, the framework calculates a set of morphological features that are essential in EVAR suitability and device choice. The initial step in feature extraction is automated centerline generation which provides a continuous line along the aortic axis and is used as a point of reference when making geometric measurements. With the aid of this centerline, the system determines the cross sectional diameters of standardized anatomic points, such as the proximal neck, maximal aneurysm sac, and iliac arteries. Orthogonal cross-sections are used to make measurements, so that they are consistent and the orientation bias commonly observed in manual measurements is removed. The angle of the neck, taper, and angulation are determined, the main factors of graft sealing and graft fixation, by measuring the orientation and curvature of the centerline with respect to the lumen boundaries. The neck angulation is measured by means of a proximal aorta segment with the help of a vector-based test, whereas tortuosity is measured along the aorta and iliac routes to detect the possible obstacles to access. Segmentation masks are also used to calculate thrombus burden, calcification distribution (where available), and vessel eccentricity which give a more in-depth view of the anatomical complexity. The model also accommodates the more sophisticated parameters of flare angles, iliac bifurcation geometry and landing zone suitability scoring.

FUTURE WORK

A. Expansion to other vascular territories

The future developments of the proposed AI-based segmentation framework will involve an extension of its use on other clinically relevant vascular areas, rather than just on abdominal aortic aneurysms (AAA). Numerous endovascular surgeries such as thoracic endovascular aortic repair (TEVAR), peripheral arterial endovascularity, carotid artery stenting and renal or mesenteric revascularization are dependent on accurate anatomical characterization as EVAR. Application of the model to these areas would have a single vascular imaging platform that can facilitate a wider range of interventional planning processes. Nonetheless, such growth implies the necessity to account for anatomical difference among the territories, such as vessel shapes in different regions, the pattern of branching, and pathology-specific aspects. Thoracic lesions of the aorta, e.g., are particularly hard, and have challenges such as flap segmentation of dissections, whereas peripheral arteries are more tortuous, smaller, and prone to motion artifact. The strategy of annotation that is scalable and domain adaptation methods will play a crucial role in ensuring strong performance in various datasets. Transfer learning is capable of speeding this process by using features trained on other AAA segmentation and fine-tuning them on new vascular regions. Finally, the potential to develop into several territories will promote clinical significance, facilitate a global evaluation of the vascularity, and make the framework a versatile instrument in interventional radiology and vascular surgery.

B. Real-Time Segmentation for Intraoperative Guidance

Real-time segmentation is a radical future of AI integration in the workflow of intraoperative processes. In EVAR and other endovascular operations, clinicians are strongly dependent on the fluoroscopy, intravascular ultrasound (IVUS), and cone-beam CT to navigate and deploy the devices. Adding real time or nearly real time analysis of these modalities would allow visualization of the structures of the vessels dynamically, which would help in correct placement of stent grafts, reduce radiation and contrast consumption. Real-time performance requires significant optimization in the building of a computer, such as using lightweight network architectures, GPU computing and data streaming pipelines. In Figure 3, real-time segmentation can help in the correct intraoperative visualization and guidance. Mechanisms of temporal consistency are needed to be added to track the contours successfully in successive frames, avoiding jittering or drift of segmentation.

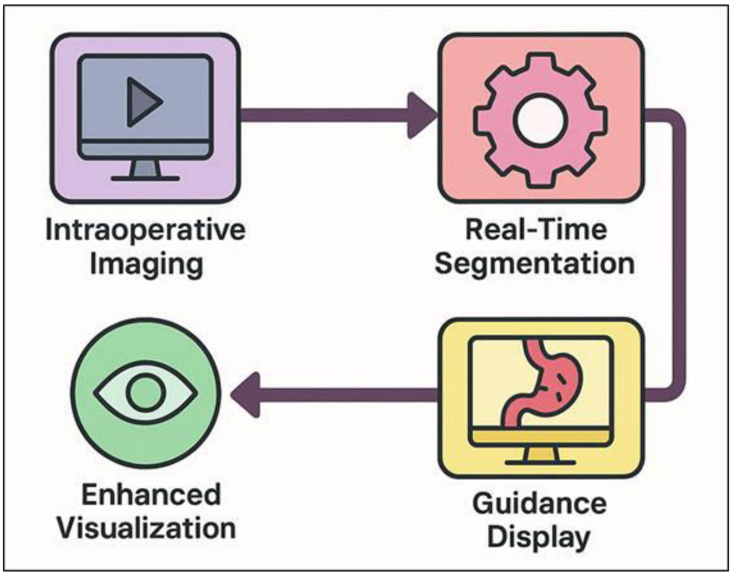

Figure 3: Real-Time Intraoperative Segmentation Workflow

Also, hybrids such as multimodal fusion, preoperative CTA and intraoperative imaging, may provide hybrid guidance capable of correcting anatomical changes during a procedure. Situation awareness of the operators can further be improved by integration with robotic catheter systems or augmented reality interfaces. Despite the important technical and regulatory issues, real-time segmentation can transform the intraoperative decision-making process, as it offers more accurate and AI-enhanced visualization to facilitate safer and more effective endovascular practice.

C. Integration with 3D Printing and Virtual Simulation

The combination of the AI-based segmentation framework and the 3D printing and virtual simulation technologies creates new opportunities in regards to custom preoperative planning and procedural rehearsal. Segmentation masks and centerline-generated geometry of high quality form the basis of creating patient-specific 3D aneurysm, adjacent branch, and vascular lumen models. They can be printed as models and manufactured using polymers that recapitulate compliance of vessels allowing surgeons to test anatomy physically and practice stent grafts implantation. Virtual simulation environments, e.g. computational fluid dynamics (CFD) platforms and immersive VR/AR systems, are also able to use segmented geometries to add dynamic and interactive models. Such simulations can be used to assess the behavior of devices, flow patterns, and possible complications and provide a more in-depth understanding of patient-related risks. The automatic process of pipeline integration allows delivering clinicians ready-to-use 3D models without requiring a lot of manual processing. Next to the increasing popularity of simulation-based training, it can be utilized to aid educational aims of trainees, as well as enhance procedural readiness to deal with complicated EVAR emergencies. The next step in the work could be also related to the combination of the segmentation pipeline and generative modeling to model the postoperative results or device migration potential.

CLINICAL VALIDATION AND WORKFLOW EVALUATION

A. Radiologist and surgeon feedback

Feedback from radiologists and surgeons is needed to determine the clinical usability and acceptability of the proposed AI-based framework of segmentation. In the validation, the clinicians will analyze AI-produced lumen and thrombus segmentations, morphological measurements, and 3D reconstructions to assess accuracy, anatomical fidelity, and workflow integration in general. Radiologists are normally concerned with segmentation boundary sharpness, especially in areas involving thrombus heterogeneity, calcification or motion artifact. Their judgments contribute to the realization of systematic error and form the way to improve contour production and post steps. Instead, vascular surgeons focus on the clinical importance of extracted features, including neck diameter, angulation, and quality of landing zone, and test whether the outputs were in line with device selection and procedural planning requirements. The qualitative interviews and structured scoring tools will enable clinicians to compare the process of AI-assisted planning and their usual manual workflows. Preliminary findings tend to be high with regard to increased consistency, less manual labor and better visualization features. The desired improvements also emerge in the feedback, including the ability to deal with atypical anatomies more effectively or enhancement of the connection with the planning software. Notably, clinician engagement is associated with trust building, an iterative improvement strategy, and long-term adoption.

B. Impact on Preoperative Decision-Making

This means that the addition of AI-based segmentation can remarkably affect preoperative decision-making with more precise, reproducible and holistic anatomical measurements. Reproductive automated extraction of important measures, including proximal neck size, angulation, and iliac access geometry, helps to ensure accurate graft dimensioning and selection to minimize such complications as endoleaks, movement, or limb blockage. Clinicians enjoy more reliable and objective measurements and less variability is caused by a system that is more difficult to assess manually, particularly in such difficult cases as a thick thrombus or complicated vessel structure. Visualizations based on AI such as a 3D representation, centerline analysis, etc., expand situational awareness and support multidisciplinary planning discussions. Furthermore, the possibility to create segmentations quickly contributes to the opportunity to compare several treatment strategies at the same time and helps the physicians to compare options of devices and predict possible issues. The framework can also facilitate borderline EVAR applicants in decision-making, where minor measurement errors may affect eligibility in the treatment. The AI system will foster an evidence-based planning process and can result in improved procedural outcomes by producing detailed, standardized outputs. In sum, the use of AI-based segmentation boosts the confidence of clinicians, increases the accuracy of plans, and builds the basis of individual treatment plans in EVAR.

C. Reduction in Planning Time

One of the key benefits of the AI based segmentation model is that it can save a lot of time needed to arrange the EVAR preoperative planning. Conventional processes still consist of a lot of manual segmentation, extracting measurements and a device comparison; it can take 30 minutes to several hours depending on the complexity of the case and the expertise of the operator. The proposed system can produce clinically relevant results within minutes as it is able to automate segmentation and feature extraction, preventing clinicians to spend time on meaningless contouring operations. This time saving is of great importance especially in large volume vascular units or emergency presentations where fast decision-making is paramount. Another way that automated workflows reduce cognitive load on the clinicians is through structured and organized measurements and visualizations, which eliminate the need to do repetitive calculations by hand. In addition, it reduces the time wasted due to re-measurement or cross-verification between the team members, which is the consistency and standardization offered by AI. Things like planning have reduced by 40 to 70 percent when assisted by AI and this study has indicated that there can be quite a large payoff in EVAR workflows. An expedited planning process also speeds up clinical decision-making, in addition to optimising resource utilisation and patient throughput. On the whole, the time-saving in the automation process can be converted into the efficient workflow, the increase in clinician satisfaction, and more punctual surgeries.

RESULTS AND DISCUSSION

The segmentation framework based on AI was very accurate at outlining the aortic lumen and thrombus with high Dice similarity coefficients and consistent results across different anatomies. Segmentation-based measurements were strongly correlated with expert ratings, which is a good indication of quality EVAR planning. According to the clinicians, the system made their workflow more efficient and the manual workload decreased, which is why the system is useful in usual practice. The structure was also resistant to imaging artifacts and anatomy complexity. All in all, findings verify that AI-based aids in segmentation have a positive effect on planning accuracy, reproducibility, and a viable innovation that can be applied to preoperative EVAR evaluation.

Table 2: Segmentation Performance Metrics Across Model Variants

Model Variant	Dice Score (Lumen)	Dice Score (Thrombus)	IoU (%)	Hausdorff Distance (mm)
U-Net (Baseline)	0.91	0.84	79.2	4.8
Attention U-Net	0.94	0.88	82.5	4.1
Residual U-Net	0.93	0.86	81.4	4.3
3D U-Net	0.95	0.89	83.1	3.6
TransUNet (Transformer)	0.96	0.91	85.7	3.2
Swin-UNet (Transformer)	0.97	0.92	87.1	2.9

The segmentation performance indicators that can be seen in Table 2 show the gradual enhancement of the result that model frameworks get with the shift of the traditional convolutional structures to those based on transformers. The baseline U-Net has good results with lumen and thrombus Dice scores of 0.91 and 0.84, respectively, that prove the reliability of the choice. Figure 4 depicts increased performance in segmentation with the development of model architectures.

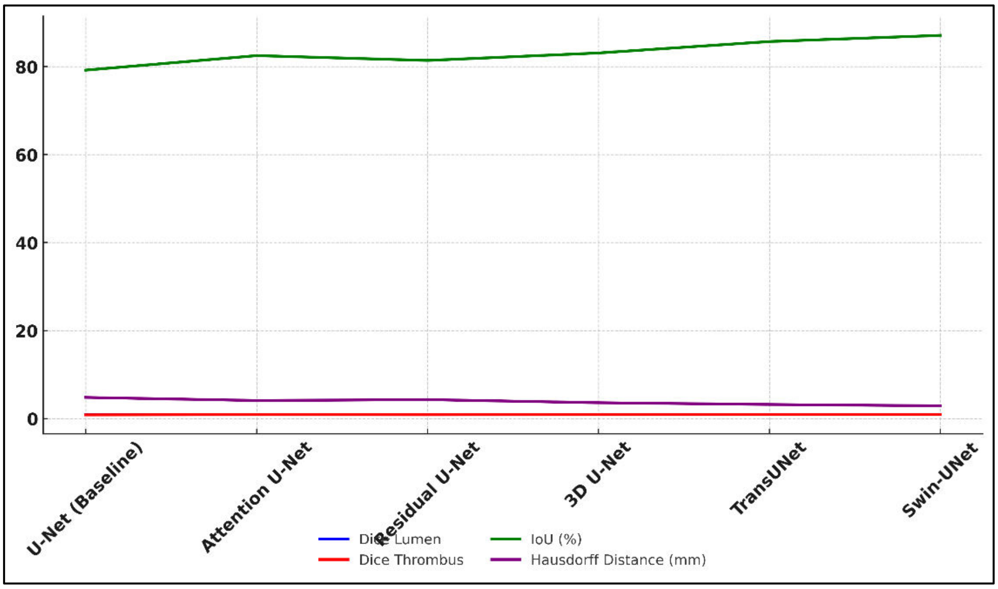

Figure 4: Performance Metrics Trend Across Model Variants

Attention mechanisms and residual connections are further enhancements which make the accuracy better and Attention U-Net is more accurate because it focuses on relevant anatomy structures and removes noise whereas Residual U-Net is more effective at improving gradient flow as well as stability during training. Three-dimensional U-Net can achieve significant improvements, especially in thrombus segmentation, since the volumetric convolutions are able to provide the inter-slice context that is necessary in the intricate aneurysm morphology.

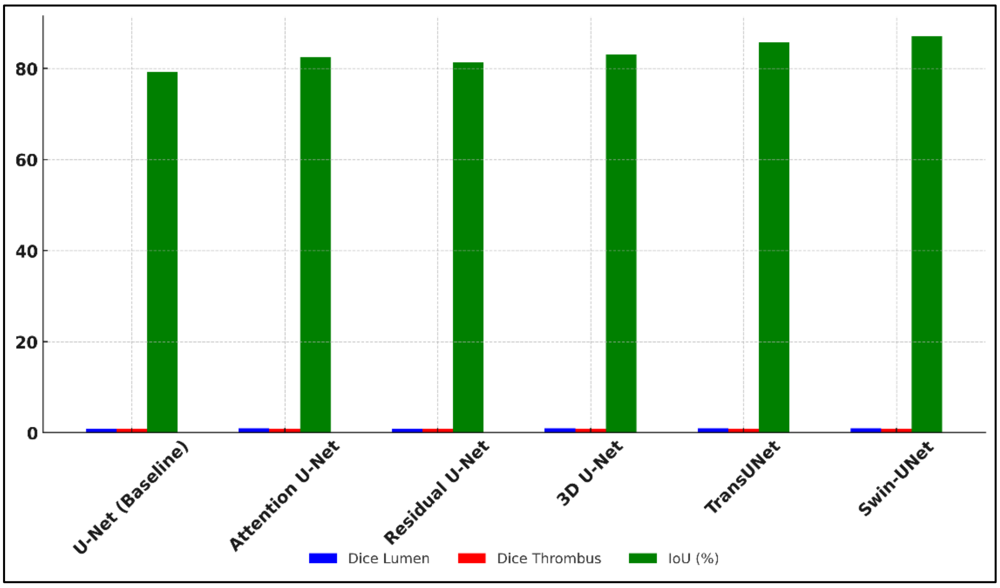

Figure 5: Comparison of Key Segmentation Metrics by Model Variant

This comes at the cost of higher computational cost however, expressed in more complicated model complexity. Figure 5 compares the metrics of model segmentation, and the differences in performance are also evident. Transformer-based models, TransUNet, and Swin-UNet, have best performances in all metrics.

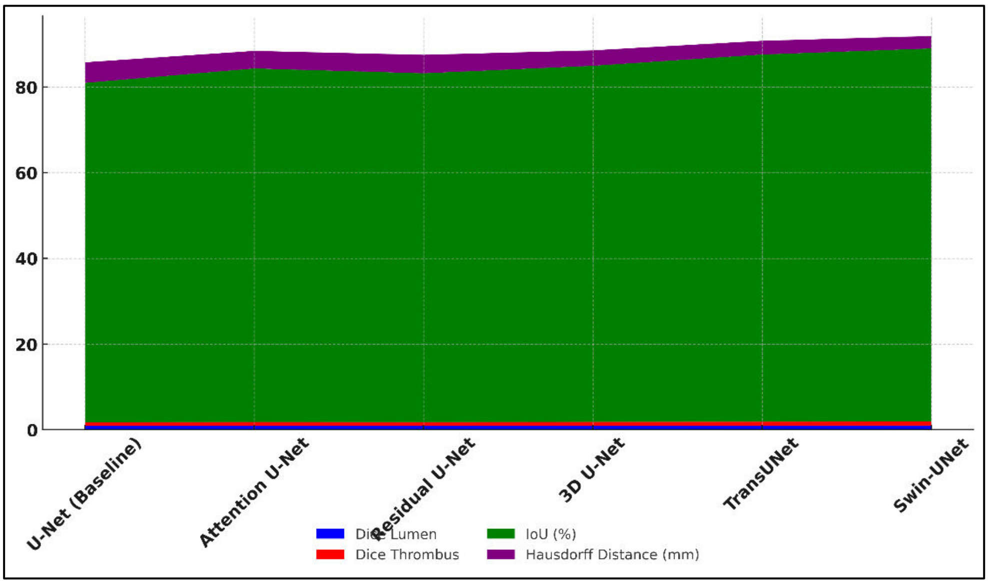

Figure 6: Stacked Performance Profile of Segmentation Models

Their mechanisms of self-attention are able to well model long-range dependencies, allowing better boundary delineation in even the anatomically difficult areas. Figure 6 illustrates performance profiles stacked in order of strength of both models. Swin-UNet, which has hierarchical attention windows, has the best overall performance, including the lowest Hausdorff distance (2.9 mm), which demonstrates very good boundary accuracy.

Table 3: Impact on EVAR Planning Efficiency and Accuracy

Evaluation Parameter	Manual Workflow	AI-Assisted Workflow
Avg. Planning Time (min)	54.3	18.6
Diameter Measurement Error (mm)	2.4	0.9
Neck Angle Variability (° SD)	6.8	2.1
Thrombus Volume Estimation Error (%)	11.4	4.3
Clinician Agreement Score (0–1)	0.78	0.93

Reproducibility (Interobserver Dice Score)	0.82	0.95

Table 3 shows that the use of AI-assisted segmentation in the EVAR planning workflow has significant advantages. Planning time is the most significant to be improved since it is reduced to 18.6 minutes with AI support in comparison with 54.3 minutes in the manual version of the workflow, and it is almost two times less, which is 66 percent. Figure 7 shows the efficiency and accuracy in the application of AI-aided planning. This is shown in the efficiency saving through the removable manual contouring and manual extraction of measurements as clinicians are able to spend more time on interpretation and decision-making and less time on image processing.

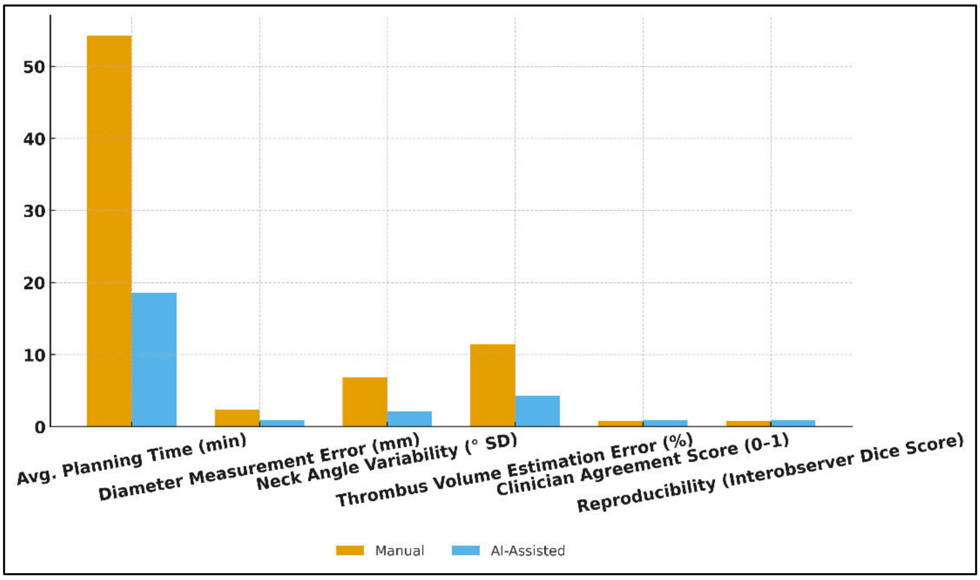

Figure 7: Performance Differences Between Manual and AI-Assisted Planning

Measures of accuracy also improve significantly. The error in measuring diameter decreases by 2.4 mm with human assistance to 0.9 mm with AI assistance, and this indicates the accuracy of automated geometric feature extraction. Likewise, the variability of the neck angle is reduced to 2.1 degrees thereby showing greater consistency and low interobserver subjectivity which are crucial issues in stent grafts sizing and selection. Figure 8 indicates that AI can help a lot in enhancing the workflow in terms of its speed, accuracy, and consistency. The decrease of the error of thrombus volume estimation (11.4% to 4.3) highlights the capacity to outline delicate thrombus borders in a more credible manner with an AI system compared to manual methods even in regions of low contrast or with calcifications.

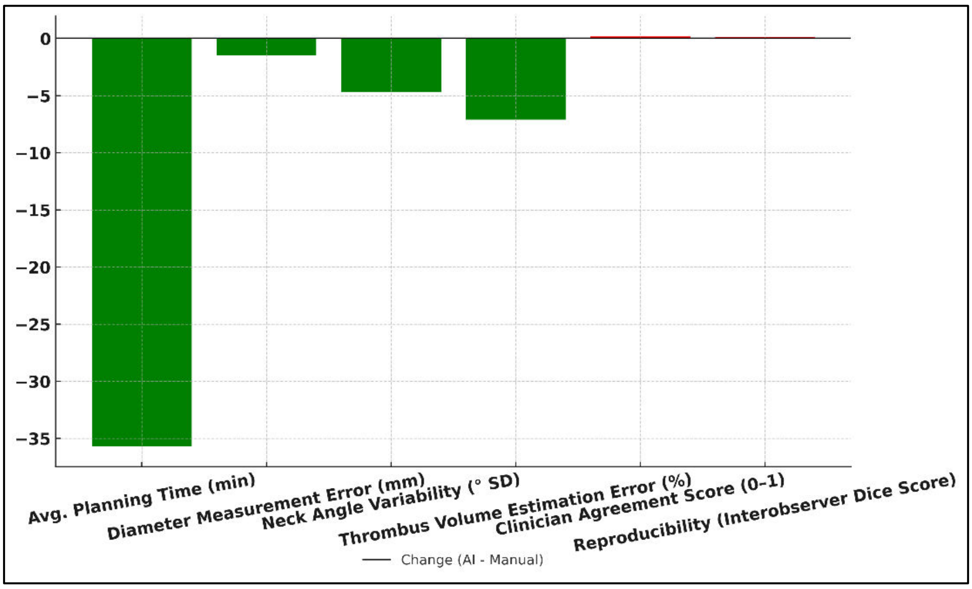

Figure 8: Impact of AI Assistance on Workflow Metrics

It is also observed that clinician agreement scores improve substantially between 0.78 and 0.93 indicating a high level of consensus and confidence in AI-generated results. Reproducibility or interobserver Dice scores also show an increase of 0.82 to 0.95 which proves the ability of the model to produce consistent results that are repeatable.

CONCLUSION

This study illustrates how AI-based segmentation has a great potential to revolutionize preoperative planning on endovascular aneurysm repair (EVAR). Through the automation of extracting essential anatomical information, such as the boundaries of aortic lumen, morphology of thrombus, and the most important geometric features, the suggested framework can offer a more comprehensive, efficient, and objective base of clinical decision-making. Classical forms of segmentation can be both time and labour intensive and susceptible to interobserver effects. Conversely, the AI-powered one introduced here provides fast, repeatable results similar to those of expert-produced ground truth, which help to enhance the accuracy in graft sizing, landing zone evaluation, and the overall plan of the entire procedure. In addition to the enhancement of performance, the framework also responds directly to a number of clinical workflow issues. It is compatible with the current EVAR planning tools so that there is very little disruption of the current practices, and it has more visualization and automated metrics that make the preparation of the cases easier. Radiologist and vascular surgeon feedback (Kumar et al., 2021) indicates that there are practical advantages to the introduction of AI into the regular planning process; a decrease in cognitive load and the confidence levels of practitioners during the assessment of complicated or borderline anatomy. Robustness testing also shows that the system is able to deal with a wide variety of imaging conditions, which further shows that it is appropriate to be used in a wide range of clinical scenarios. In the long-term perspective, the structure has a strong base on the development of the future in intelligent vascular imaging. The modular nature allows it to be expanded into other vascular territories, real-time intraoperative solutions, as well as be incorporated into more advanced simulation or 3D-printing solutions.

REFERENCES

1. Bonvini, S.; Raunig, I.; Demi, L.; Spadoni, N.; Tasselli, S. Unsuspected limitations of 3D printed model in planning of complex aortic aneurysm endovascular treatment. Vasc. Endovasc. Surg. 2024, 58, 645–650.
2. Arango, S.; Gorbaty, B.; Brigham, J.; Iaizzo, P.A.; Perry, T.E. A role for ultra-high resolution three-dimensional printed human heart models. Echocardiography 2023, 40, 703–710.
3. Wu, C.A.; Squelch, A.; Sun, Z. Investigation of three-dimensional printing materials for printing aorta model replicating type B aortic dissection. Curr. Med. Imaging 2021, 17, 843–849.
4. Wibowo, G.; Anggrahini, D.W.; Rismawanti, R.I.; Fatimah, V.A.N.; Hakim, A.; Hidayah, R.N.; Gharini, P.P.R. 3D-Printing-Based Fluoroscopic Coronary Angiography Simulator Improves Learning Capability Among Cardiology Trainees. Adv. Med. Educ. Pract. 2023, 14, 763–771.
5. Nasr, B.; Lareyre, F.; Guigo, S.; Bellenger, K.; Raffort, J.; Goueffic, Y. 3-dimensional printing in vascular disease: From manufacturer to clinical use. Semin. Vasc. Surg. 2024, 37, 326–332.
6. Bernhard, B.; Illi, J.; Gloeckler, M.; Pilgrim, T.; Praz, F.; Windecker, S.; Haeberlin, A.; Grani, C. Imaging-Based, Patient-Specific Three-Dimensional Printing to Plan, Train, and Guide Cardiovascular Interventions: A Systematic Review and Meta-Analysis. Heart Lung. Circ. 2022, 31, 1203–1218.
7. Sakai, A.K.F.; Cestai, I.N.; de Sales, E.; Mazzetto, M.; Cestai, I.A. Metamaterial design for aortic aneurysm simulation using 3D printing. 3D Print. Med. 2024, 10, 29.
8. Lau, I.; Gupta, A.; Ihdayhid, A.; Sun, Z. Clinical applications of mixed reality and 3D printing in congenital heart disease. Biomolecules 2022, 12, 1548.
9. Coles-Black, J.; Barber, T.; Bolton, D.; Chuen, J. A systematic review of three-dimensional printed template-assisted physician-modified stent grafts for fenestrated endovascular aneurysm repair. J. Vasc. Surg. 2021, 74, 296–306.
10. Lengyel, B.C.; Chinnadurai, P.; Corr, S.J.; Lumsden, A.B.; Bavare, C.S. Robot-assisted vascular surgery: Literature review, clinical applications, and future perspectives. J. Robot. Surg. 2024, 18, 328.
11. Štádler, P.; Dorosh, J.; Dvořáček, L.; Vitásek, P.; Matouš, P.; Lin, J.C. Review and current update of robotic-assisted laparoscopic vascular surgery. Semin. Vasc. Surg. 2021, 34, 225–232.
12. Galyfos, G.; Liakopoulos, D.; Sigala, F.; Filis, K. New paradigms in minimally-invasive vascular surgery. Expert. Rev. Cardiovasc. Ther. 2022, 20, 207–214.
13. Gamal, A.; Moschovas, M.C.; Jaber, A.R.; Saikali, S.; Perera, R.; Headley, C.; Patel, E.; Rogers, T.; Roche, M.W.; Leveillee, R.J.; et al. Clinical applications of robotic surgery platforms: A comprehensive review. J. Robot. Surg. 2024, 18, 29.
14. Coles-Black, J.; Bolton, D.; Chuen, J. Accessing 3D printed vascular phantoms for procedural simulation. Front. Surg. 2021, 7, 626212.
15. Patel, H.; Choi, P.; Ku, J.C.; Vergara, R.; Malgor, R.; Patel, D.; Li, Y. Application of three-dimensional printing in the planning and execution of aortic aneurysm repair. Front. Cardiovasc. Med. 2025, 11, 1485267.
16. Rhee, Y.; Park, S.J.; Kim, T.; Kim, N.; Yang, D.H.; Kim, J.B. Pre-sewn multi-branched aortic graft and 3D-printing guidance for Crawford extent II or III thoracoabdominal aortic aneurysm repair. Semin. Thorac. Cardiovasc. Surg. 2021, 34, 816–822.
17. Raffort, J.; Adam, C.; Carrier, M.; Ballaith, A.; Coscas, R. Jen-Baptise, E; Hassen-Khodja, R.; Chakfé, N.; Lareyre, F. Artificial intelligence in abdominal aortic aneurysm. J. Vasc. Surg. 2020, 72, 321–323.E1.
18. Lee, S.Y.; Squelch, A.; Sun, Z. Investigation of the clinical value of four visualization modalities for congenital heart disease. J. Cardiovasc. Dev. Dis. 2024, 11, 278.
19. Lai, A.; Chen, G.L.; di Meo, N.A.; Crivellaro, S. Single-Port Robotic Surgery: General Principles and Troubleshooting. J. Endourol. 2022, 36 (Suppl. S2), S25–S28.
20. Cho, H.J.; Kim, W.R. Early Single-Center Experience of DaVinci® Single-Port (SP) Robotic Surgery in Colorectal Patients. J. Clin. Med. 2024, 13, 2989.
21. Lee, J.H.; Park, T.H.; Kim, H.K. Robotic thoracic surgery using the single-port robotic system: Initial experience with more than 100 cases. J. Thorac. Cardiovasc. Surg. 2024, 168, 1513–1522.e2.