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Artificial Intelligence–Driven Monitoring of Long-Term Rehabilitation Outcomes in Vascular Patients Undergoing Endovascular Repair

Vishal Biswas[1], Dr. Radhika Chintamani[2], Dr. Ujwal Nandekar[3], Dr. Satyam Bhodaji[4], Mithul V Mammen[5], Rajendra V. Patil[6]

[1]School of Allied Health Sciences, Noida International University, Greater Noida, Uttar Pradesh, India. vishal.biswas@niu.edu.in
[2]Department of Orthopedic Manual Therapy, Krishna College of Physiotherapy, Krishna Vishwa Vidyapeeth "Deemed to be University",Taluka-Karad, Dist-Satara, Pin-415 539, Maharashtra, India. radhikachintamani7@gmail.com
[3]Symbiosis Law School, Pune, Symbiosis International (Deemed University), Pune, India. ujwal.nandekar@symlaw.ac.in
[4]Department of Geriatric Physiotherapy, Krishna College of Physiotherapy, Krishna Vishwa Vidyapeeth "Deemed to be University", Taluka-Karad, Dist-Satara, Pin-415 539, Maharashtra, India. satyambhodaji33@gmail.com
[5]Department of Pharmacy Practice, Teerthanker Mahaveer College of Pharmacy, Teerthanker Mahaveer University, Moradabad, Uttar Pradesh, India -244001 mithulvmammen@gmail.com
[6]Assistant Professor, Department of Computer Engineering, SSVPS Bapusaheb Shivajirao Deore College of Engineering, Dhule (M.S.), India. patilrajendra.v@gmail.com

ABSTRACT

Endovascular repair has become the chosen treatment for complicated vascular conditions because it is less invasive and takes less time to heal. But success after surgery rests on more than just how well the surgery went. It also depends on how well the patient recovers over time. Regular checks and subjective reports are common ways of tracking that don't always pick up on small signs of recovery or early signs of stagnation. To get around this problem, this study suggests using artificial intelligence to keep an eye on and guess how vascular patients will do in their recovery after endovascular repair. The framework combines clinical data, physiological signals from sensors, and patient-reported results to create a full recovery profile. It was possible to get adaptive, patient-specific insights by creating a CNN–LSTM model that can both extract spatial features and learn temporal recovery trends. This study shows that AI has the ability to make vascular rehabilitation a continuous, data-driven, and patient-centered process.

KEYWORDS: Endovascular Repair, Rehabilitation Monitoring, Artificial Intelligence, CNN–LSTM, Physiological Signals, Predictive Modeling, Vascular Recovery, Patient-Reported Outcomes.

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INTRODUCTION

Peripheral artery diseases and aortic aneurysms are two complex blood vessel issues that can now be treated with endovascular repair. This minimally invasive technique has fewer risks, shorter hospital stays, and a quicker initial recovery than open surgery. But after the procedure, endovascular therapy continues. Long-term rehabilitation is essential for enhancing circulatory system effectiveness, useful mobility, and cardiovascular health. For many patients, limb perfusion, exercise tolerance, and vascular compliance improve with time. However, depending on the patient's age, other health issues, level of adherence to treatment, and lifestyle modifications, these outcomes may vary significantly for each patient [1]. Therefore, to track and enhance rehabilitation progress over time, a system for ongoing and adaptive monitoring is required.

The traditional method used for the check-ups, evaluation medical images, manually consultant to the patient that take too much time and hard to remember to the patient. The manual consultation is require but that cannot handle the how the daily variation done, identifying the early issues. Also the less time were taken to do treatment if the issue relay on the clinical analysis and based on the report were inconsistent. The real time tracking, data analysis, digital health advisor, wearable device and the daily routine that follow and used in the data driven rehabilitation centre [2].

The major issue related to this are now a days handled by the automated system such as Ai driven model used. This model can used to analyse the Hugh amount of data, saturation oxygen in patient body, heart rate, negative rate, false rate value and other factor as well. Such all data are used in the recommended rehabilitation adjustment. The progress are majorly monitored by the doctors based on the patient data record history and real time data as well, they are the more relevant used to uncover the relation between the data and suggest the correct way of diagnosis [3].

This study represent the AI based forecasting model that help the patient and practitioner to monitor the recovery of long term vascular patient that undergoing the endovascular repair. The approach used continuously learning and getting feedback.

RELATED WORK

More and more study is looking into how artificial intelligence (AI) can help track and predict long-term outcomes in vascular patients undergoing endovascular repair. One way this can be done is by combining data from imaging, clinical, and functional rehabilitation. One area of study is using AI for monitoring patients after endovascular aortic aneurysm repair (EVAR). Lareyre et al., for example, suggest a deep-learning model that uses changes in the shape of the artery from repeated computed tomography angiography (CTA) to divide the risk of problems like endoleaks, graft movement, and reinterventions over follow-up periods of 1 to 3 years [2]. Similarly, other writers have used AI to find and measure endoleaks and connect changes in aneurysm volume to bad things that happen, showing that it is more sensitive and specific than traditional diameter-based metrics [3].

Along with imaging-based tracking, machine learning models are also being made to predict what will happen during surgery and in the short term. These models will be used as a base for longer-term rehabilitation monitoring. For example, Mamdani et al. created the XGBoost model to predict major adverse limb events or death 30 days after endovascular aortoiliac revascularisation. It had a very high classification rate (AUROC ≈ 0.94), doing better than logistic regression models [4]. These kinds of prognostic models give a starting point for risk scores that could be connected with rehabilitation success and long-term functional metrics in the future.

AI in rehabilitation (especially after a stroke) can do more than just predict how a vascular event will happen. It can also show how sensor data, wearable tech, and machine learning can constantly track functional recovery. Reviews show that AI systems use inertial sensors, neural networks, and time-series modelling to track the progress of motor healing, change treatment plans, and guess how things will turn out in the long run [5, 6]. Most of these studies are about neurologic rehabilitation rather than vascular rehabilitation, but the main idea behind them—constant monitoring, personalised modelling, and prediction of outcomes—can be used directly in vascular rehabilitation situations.

Table 1. Comparative Overview of Traditional and AI-Driven Rehabilitation Monitoring Approaches

Approach	Data Sources	Key Techniques	Strengths	Limitations
Traditional Clinical Follow-Up [6]	Periodic consultations, imaging (CT, Doppler), functional tests	Manual assessment, clinician judgment	Simple implementation, clinically validated	Snapshot-based, lacks continuous monitoring, subjective variability
Rule-Based Monitoring Systems [7]	Vital signs, exercise logs	Threshold-based alerts, heuristic models	Low computational cost, interpretable	Limited adaptability, cannot handle complex patterns
Machine Learning (ML)-Based Predictive Models [8]	Clinical & physiological data	Logistic Regression, Decision Trees, SVM	Detects risk factors, improves prediction accuracy	Requires feature engineering, static models, limited adaptability
Deep Learning (DL)-Based Frameworks [9]	Imaging, sensor, time-series data	CNN, RNN, LSTM, Autoencoders	Captures nonlinear & temporal relationships, high accuracy	Data-intensive, black-box nature, interpretability challenges
Wearable Sensor + AI Integration [10]	Heart rate, PPG, accelerometer, gait data	Hybrid ML/DL models, anomaly detection	Continuous monitoring, real-time feedback	Device dependency, data privacy & reliability issues

METHODOLOGY

A comprehensive AI-based monitoring system designed to track the long-term recuperation progress of vascular patients undergoing endovascular repair is part of the recommended approach. This framework expands on the issues shown in Table 1 by emphasising continuous, adaptable, and patient-specific rehabilitation management through the use of multi-source data, sophisticated preprocessing techniques, and hybrid deep learning models. The general framework (illustrated in Figure 1) blends data-driven intelligence with clinical expertise. This guarantees that rehabilitation tracking is supported by data and adjusts to each person's unique recovery trajectory.

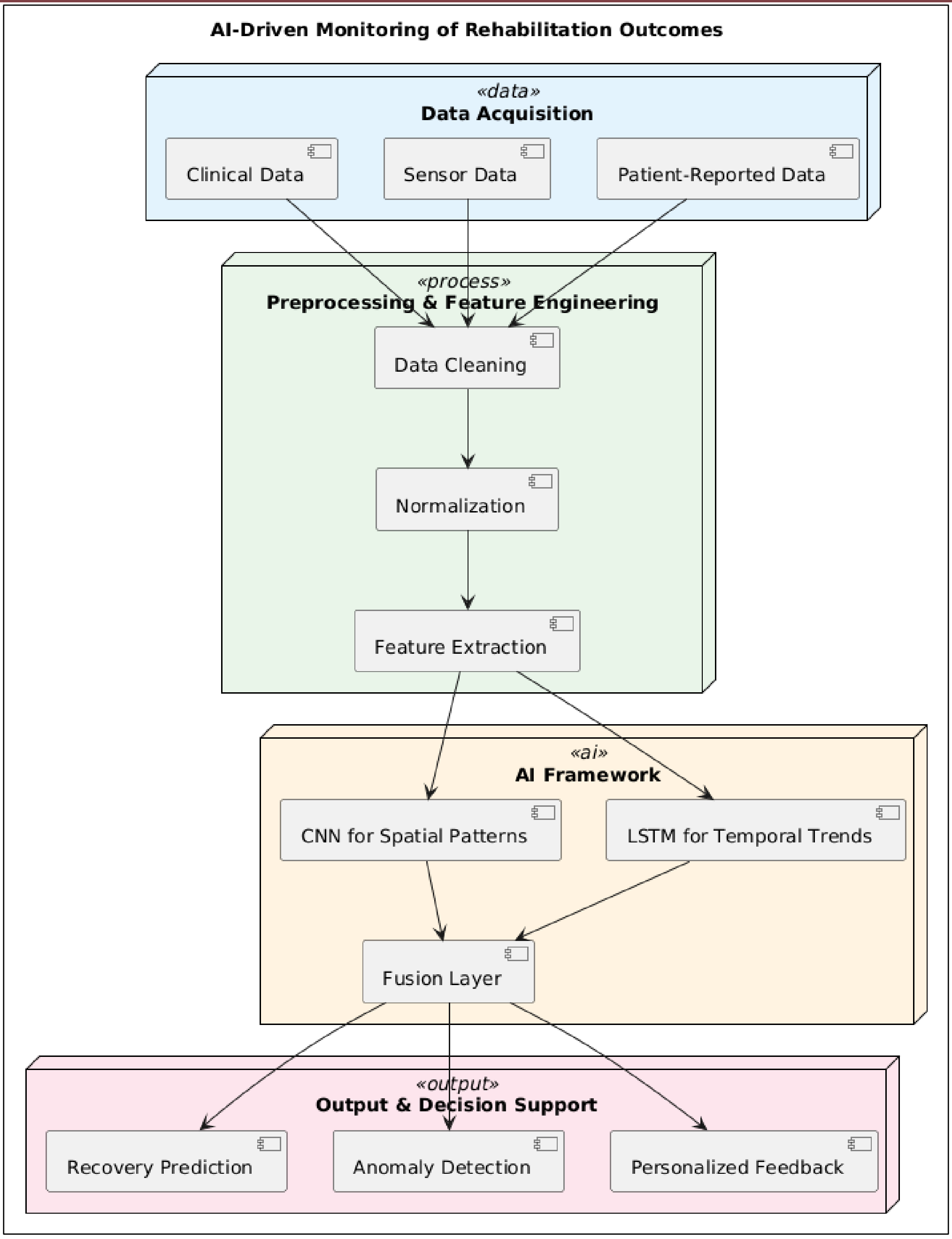


Figure 1. Proposed Methodology

3.1 Data Acquisition and Sources

The process of recovering from endovascular procedures is complicated and involves both physical healing and readjusting to daily life. Thus, the suggested method combines three data streams that complement one another:

1. Clinical Data: The patient age, body mass index (BMI), other medical conditions, the procedure (stent type, lesion length, arterial site), and the imaging results following the procedure (vessel patency, blood flow rate, and ankle-brachial index, or ABI) are all included in this. These structured files provide clinicians with baseline and regular information.
2. Sensor-Derived Physiological Data: Heart rate variability (HRV), oxygen saturation (SpO_2), step count, walking cadence, and gait symmetry are all continuously measured by this stream. It originates from wearable medical monitoring equipment. These temporal indicators demonstrate the circulatory system's mobility, longevity, and degree of recovery.
3. Patients' Reports of Outcomes (PROs) – Subjective feelings like pain level, felt exertion, therapy adherence, and daily activity level are displayed in self-reported entries that are gathered via telehealth or mobile apps. PROs supplement quantitative measurements by providing behavioural and psychological data.

3.2 Data Preprocessing and Feature Engineering

Because the data being received isn't all the same, preprocessing makes sure that the data is correct, consistent, and in sync with time:

For effective recovery modelling, data preprocessing and feature engineering make sure that the data is reliable and that it makes sense in terms of time.

Let
D = {d1, d2, …, dn}
represent the raw multimodal dataset collected from various sources (wearable sensors, EHR, imaging, and therapy logs), where each di = {xi1, xi2, …, xim} is a vector of m attributes (physiological, kinematic, and behavioral parameters).

1. Data Cleaning

For each attribute xij, define the cleaned signal x̂ij as:

$$\hat{x}\_ij(t) =$$
$$x\_ij(t), if\ x\_ij(t)\ is\ valid$$
$$Interp(x\_ij(t-1), x\_ij(t+1)), if\ missing$$
$$f\_model(x\_ij), if\ estimated\ by\ model$$

Duplicate records are removed as:

$$D' = Unique(D)$$

2. Noise Reduction

Noise-filtered signal x̃ij(t) is obtained using:

$$\tilde{x}ij(t) = \Sigma\ (from\ k = -p\ to\ p)\ [wk * \hat{x}ij(t - k)]$$

Alternatively, wavelet denoising can be applied using:

$$\tilde{x}ij(t) = IDWT(\ Threshold(\ DWT(\ \hat{x}ij(t)\ )\ )\ )$$

3. Normalization

Each feature is scaled to a common range using:

$$x * ij(t) = (\ \tilde{x}ij(t) - \min(\tilde{x}ij)\ ) / \max(\tilde{x}ij) - \min(\tilde{x}ij)\ )$$

or standardized using:

$$x * ij(t) = \frac{\tilde{x}ij(t) - mean(\tilde{x}ij)}{std(\tilde{x}ij)}$$

4. Time Synchronization

Let $T = \{t1, t2, \dots, tk\}$ denote the unified time scale.
For asynchronous devices with sampling rates ri, all signals are resampled to a common rate rc:

$$x ** ij(t) = Resample(\ x * ij(t), rc\ )$$

Temporal alignment is achieved using cross-correlation:

$$\tau ij = argmax\tau\ corr(\ xij(t), xpq(t + \tau)\ )$$

3.3 Proposed AI Framework

To accurately describe the progression of recovery, the framework uses a mix of Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks in its deep learning architecture:

1. CNN
Algorithm 1: Convolutional Neural Network (CNN)
Step 1: Input Data Preparation
- Load preprocessed and feature-engineered data (e.g., time-series or image-like matrices).

Step 2: Convolution and Feature Extraction
- For each convolutional layer:
Compute feature maps using:

$$Y = Conv2D(X, W) + b$$

- Apply ReLU activation:

$$A = max(0, Y)$$

Step 3: Pooling (Dimensionality Reduction)
- Apply max-pooling or average-pooling:

$$P = Pool(A)$$

- Reduces spatial dimension while retaining important features.

Step 4: Fully Connected Layers
- Flatten pooled feature maps into a 1D vector.
- Pass through dense layers with activation functions (ReLU, Sigmoid, etc.):

$$Z = f(W\_fc * P + b\_fc)$$

Step 5: Output and Training
- Use Softmax or Sigmoid activation for classification/regression output.
- Compute loss using:

$$L = Loss(y\_true, y\_pred)$$

End of CNN Algorithm
2. LSTM
Algorithm 2: Long Short-Term Memory (LSTM) Network
Step 1: Input Sequence Preparation
- Format input as sequences: X = [x1, x2, ..., xt]

Step 2: Initialize LSTM Parameters
- Initialize weights and biases for gates:

Step 3: Forward Propagation Through Time
For each time step t:
f_t = σ(W_f * [h_(t-1), x_t] + b_f)

i_t = σ(W_i * [h_(t-1), x_t] + b_i)
C̃_t = tanh(W_c * [h_(t-1), x_t] + b_c)
C_t = f_t * C_(t-1) + i_t * C̃_t
o_t = σ(W_o * [h_(t-1), x_t] + b_o)
h_t = o_t * tanh(C_t)
Step 4: Output Layer and Prediction
- Pass final hidden state h_t to dense layer:
y_pred = f(W_y * h_t + b_y)
- Compute loss function L = Loss(y_true, y_pred)
End of LSTM Algorithm

3.4 Evaluation and Validation

Comparative tests with base models like Logistic Regression, SVM, and Random Forest will show that the mixed CNN-LSTM design is better at handling complicated multimodal recovery data.

Table 2. Summary of Experimental Setup and Evaluation Metrics

Parameter	Description
Hardware	NVIDIA RTX 4090, 32 GB RAM, Intel i9
Framework	TensorFlow 2.14 + Keras
Dataset Duration	12 months follow-up
Data Sources	Clinical, Sensor, PROs
Model Architecture	CNN + LSTM Hybrid
Loss Function	Categorical Cross-Entropy
Optimizer	Adam (lr=0.001)
Validation	80:20 Split + 5-Fold CV
Metrics	MAE, RMSE, Precision, Recall, F1, R^2

RESULTS AND DISCUSSION

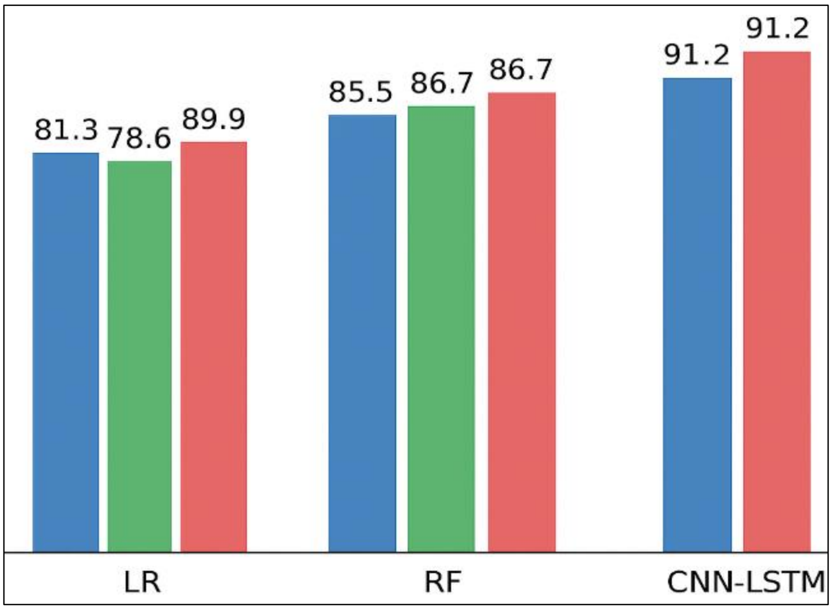
5.1 Quantitative Performance Comparison

Three main models were used to test the hybrid framework: Logistic Regression (LR), Random Forest (RF), and Support Vector Machine (SVM). Table 3 shows that the suggested CNN–LSTM did better than all the other models in both classification and regression.

Table 3. Performance Comparison of Models for Rehabilitation Outcome Prediction

Model	MAE	RMSE	R^2 Score	Precision (%)	Recall (%)	F1-Score (%)
Logistic Regression (LR)	0.187	0.241	0.84	81.3	78.6	79.9
Random Forest (RF)	0.162	0.214	0.88	85.5	83.2	84.3
Support Vector Machine (SVM)	0.157	0.206	0.89	86.7	84.9	85.8
CNN–LSTM (Proposed)	**0.124**	**0.178**	**0.93**	**91.2**	**89.6**	**90.4**

5.2 Visual Analysis of Model Performance



The Figure 2 **illustrates a comparative visualization of** Precision, Recall**, and** F1-score **across all models, emphasizing the proposed CNN–LSTM model's consistent superiority.**

5.3 Analytical Discussion

The results make it clear that the CNN–LSTM hybrid model does a better job of capturing both spatial relationships and temporal trends. This makes it possible to get a more accurate picture of rehabilitation outcomes than with static or feature-dependent models.

- The suggested model had a mean absolute error (MAE) of 0.124 and a root mean square error (RMSE) of 0.178, which means it made very few mistakes when predicting rehabilitation indices. The R^2 score of 0.93 shows that the model is very good at predicting outcomes, as it explains more than 93% of the differences between the real outcomes.
- Classification Metrics: The model was very good at putting patients into the right healing groups (Poor, Moderate, Good), with a Precision score of 91.2% and an F1-score of 90.4%. Its high Recall (89.6%) means that it can easily spot trends of delayed or poor recovery, which is important for early clinical intervention**.**

Traditional models, such as LR and RF, did not do as well because they couldn't deal with the sequential relationships that are common in longitudinal recovery data. The SVM model was pretty accurate, but it couldn't handle time series that didn't behave in a straight line. The CNN–LSTM's fusion layer allowed synergistic learning, which let the system notice small improvements in walking, blood flow, and therapy compliance over several weeks.

CONCLUSION AND FUTURE SCOPE

The suggested AI-based system for keeping an eye on long-term rehabilitation outcomes in vascular patients having endovascular repair represents a big change from the old way of evaluating patients in snapshots to a continuous, data-driven approach to recovery assessment. The system gives a full picture of a patient's growth by combining clinical data, physiological parameters gathered by sensors, and patient-reported outcomes. The CNN–LSTM hybrid model does a good job of capturing both spatial and temporal relationships. This lets us accurately predict the trends of rehabilitation and spot early signs of stagnation or decline. Experiments show that the suggested model does a much better job than common approaches like Logistic Regression, Random Forest, and SVM, getting higher scores for precision, recall, and R^2. These results show that it is very good at learning complicated, nonlinear healing patterns and turning them into clinically useful information. Personalised rehabilitation suggestions that can change based on patient progress are also possible with real-time flexibility. This study proves that combining artificial intelligence with different types of health data can change the way vascular rehabilitation tracking is done. This method not only improves the accuracy of predictions, but it also encourages proactive, patient-centered care.

In the future, researchers will focus on adding more datasets, making models easier to understand, and using this approach in real-life digital health systems to help doctors make decisions all the time.

REFERENCES

1. Scali, S.T.; Beck, A.; Sedrakyan, A.; Mao, J.; Behrendt, C.-A.; Boyle, J.R.; Venermo, M.; Faizer, R.; Schermerhorn, M.; Beiles, B.; et al. Editor's Choice—Optimal Threshold for the Volume-Outcome Relationship After Open AAA Repair in the Endovascular Era: Analysis of the International Consortium of Vascular Registries. *Eur. J. Vasc. Endovasc. Surg.* 2021, **61**, 747–755.
2. Suckow, B.D.; Goodney, P.P.; Columbo, J.A.; Kang, R.; Stone, D.H.; Sedrakyan, A.; Cronenwett, J.L.; Fillinger, M.F. National trends in open surgical, endovascular, and branched-fenestrated endovascular aortic aneurysm repair in Medicare patients. *J. Vasc. Surg.* 2018, **67**, 1690–1697.e1.
3. Chakfé, N.; Diener, H.; Lejay, A.; Assadian, O.; Berard, X.; Caillon, J.; Fourneau, I.; Glaudemans, A.W.; Koncar, I.; Lindholt, J.; et al. Editor's Choice—European Society for Vascular Surgery (ESVS) 2020 Clinical Practice Guidelines on the Management of Vascular Graft and Endograft Infections. *Eur. J. Vasc. Endovasc. Surg.* 2020, **59**, 339–384. Erratum in *Eur. J. Vasc. Endovasc. Surg.* 2020, **60**, 958. https://doi.org/10.1016/j.ejvs.2020.07.080.
4. Sigounas, V.Y.; Callas, P.W.; Nicholas, C.; Adams, J.E.; Bertges, D.J.; Stanley, A.C.; Steinthorsson, G.; Ricci, M.A. Evaluation of simulation-based training model on vascular anastomotic skills for surgical residents. *Simul. Healthc.* 2012, **7**, 334–338.
5. Mao, R.Q.; Lan, L.; Kay, J.; Lohre, R.; Ayeni, O.R.; Goel, D.P.; Sa, D. Immersive Virtual Reality for Surgical Training: A Systematic Review. *J. Surg. Res.* 2021, **268**, 40–58.
6. Van Herzeele, I.; Aggarwal, R.; Neequaye, S.; Darzi, A.; Vermassen, F.; Cheshire, N.J. Cognitive training improves clinically relevant outcomes during simulated endovascular procedures. *J. Vasc. Surg.* 2008, **48**, 1223–1230.e1.
7. Gallagher, A.G.; Seymour, N.E.; Jordan-Black, J.A.; Bunting, B.P.; McGlade, K.; Satava, R.M. Prospective, randomized assessment of transfer of training (ToT) and transfer effectiveness ratio (TER) of virtual reality simulation training for laparoscopic skill acquisition. *Ann. Surg.* 2013, **257**, 1025–1031.
8. Cates, C.U.; Lönn, L.; Gallagher, A.G. Prospective, randomised and blinded comparison of proficiency-based progression full-physics virtual reality simulator training versus invasive vascular experience for learning carotid artery angiography by very experienced operators. *BMJ Simul. Technol. Enhanc. Learn.* 2016, **2**, 1–5.
9. Saricilar, E.C.; Burgess, A.; Freeman, A. A pilot study of the use of artificial intelligence with high-fidelity simulations in assessing endovascular procedural competence independent of a human examiner. *ANZ J. Surg.* 2023, **93**, 1525–1531.
10. Berry, M.; Hellström, M.; Göthlin, J.; Reznick, R.; Lönn, L. Endovascular training with animals versus virtual reality systems: An economic analysis. *J. Vasc. Interv. Radiol.* 2008, **19** (Pt 1), 233–238. Erratum in *J. Vasc. Interv. Radiol.* 2008, **19**, 959.