



Clinical outcome prediction of Contour Neurovascular System treatment based on pre-treatment geometric and hemodynamic characteristics

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Received: 9 January 2026 / Accepted: 30 July 2026

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Abstract

Purpose The contour neurovascular system (CNS) is increasingly used for endovascular treatment of intracranial aneurysms, but outcome and post-treatment device behavior vary between patients. This study investigated whether pre-treatment geometric and hemodynamic characteristics from image-based blood flow simulations are associated with clinical outcome and follow-up CNS shape modifications.

Methods Pre-treatment vascular geometries and blood flow simulations were analyzed in 39 CNS-treated cases. Geometric, hemodynamic, and ostium-flow clustering features were extracted, followed by global feature thinning to reduce redundancy. Associations with binary clinical outcome and follow-up shape modifications (SM1–SM3) were assessed using nonparametric univariate statistics with false discovery rate correction. Exploratory outcome discrimination was evaluated using a support vector machine classifier.

Results Aneurysm geometry showed the strongest association with clinical outcome. Smaller dome and ostium areas were associated with positive outcome (Cliff's $\delta = -0.57$ and -0.43), while hemodynamic parameters showed weaker but directionally consistent trends, including lower peak outflow velocity, and reduced inflow intensity. Shape-modification patterns differed across deformation classes. SM1 and SM2 showed no FDR-significant features but moderate effects for aneurysm geometry and selected hemodynamic metrics. SM3 showed the strongest associations with oscillatory flow characteristics ($\delta \approx 0.56$ – 0.57) and peripheral outflow dominance. Exploratory machine learning showed limited, non-significant outcome discrimination (mean AUC = 0.57), with selected features consistent with univariate findings.

Conclusion Pre-treatment geometric and hemodynamic characteristics are linked not only to clinical outcome but also to post-treatment CNS shape modifications. By linking pre-operative flow conditions to follow-up device behavior, this study improves the understanding of hemodynamic factors associated with CNS shape modifications and suggests that simulation-based analysis may support future patient-specific treatment planning using exclusively pre-operative data.

Keywords Intracranial aneurysms · Contour neurovascular system · Treatment outcome prediction · Support vector machine classifier · Image-based blood flow simulation

Introduction

Intracranial aneurysms (IAs) are local dilations of cerebral blood vessels and carry a risk of rupture, which may result in severe morbidity or fatal outcome [1, 2]. Consequently, their treatment represents a major field of neurointerventional research. The therapy of wide-necked bifurcation

aneurysms is particularly challenging, as established treatment approaches such as coil embolization are associated with relatively low occlusion rates [3, 4].

To address these limitations, novel endovascular treatment devices have been developed. One of these devices is the intrasaccular contour neurovascular system (CNS) (Stryker, Portage, USA), whose safety and efficacy have been evaluated in clinical studies and are being further investigated.

Initial clinical studies have demonstrated promising results for the CNS, with a retrospective review of 131 cases reporting the device as safe and effective and a pooled

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adequate occlusion rate of 84% [5]. Early *in silico* studies further confirmed its hemodynamic effect by showing effective intra-aneurysmal flow disruption [6, 7]. Nevertheless, incomplete occlusion, device displacement, and CNS deformation after initially successful implantation have been reported and may require further therapeutic intervention [9–11]. Larsen et al. [8] specifically investigated CNS deformation and demonstrated that larger IA neck diameters and deformation patterns are significantly associated with recurrence. These findings suggest that aneurysm morphology, hemodynamic flow reduction, and device-related deformation may jointly influence treatment outcome.

Thus, the present study investigates whether pre-treatment geometric and hemodynamic characteristics, with a particular focus on ostium-related flow features, are associated with clinical outcome and follow-up CNS shape modifications. In addition, an exploratory support vector machine analysis was performed to assess whether these exclusively pre-treatment features contain predictive information for future outcome prediction.

Materials and methods

Medical data and grouping procedure

This study included 39 intracranial aneurysms in 38 patients treated with the CNS between 12/2018 and 09/2024. Pre-treatment imaging data were derived from 3D rotational angiography (3D-RA) datasets acquired at the University Medical Center Schleswig–Holstein using a biplane angiography system (Azurion, Philips, Amsterdam, The Netherlands) with a reconstructed isotropic voxel size of 0.16 mm. Treated CNS sizes were 7, 9, and 11 mm. Post-treatment and 24 h follow-up imaging were available for clinical assessment. The median imaging follow-up was 574 days, with an interquartile range of 382–836 days. Thirty-eight of 39 cases had at least 3 months of follow-up, 36 had at least 6 months, and 30 had at least 12 months.

Clinical outcome was assessed retrospectively based on all available follow-up imaging. The last available imaging follow-up was used unless clinical worsening had already been documented earlier. Negative outcome was defined as clinically relevant worsening during follow-up, including retreatment, incomplete or progressive residual aneurysm filling, recurrence, or unfavorable aneurysm/device deformation. Cases without documented worsening until the last available follow-up were classified as positive outcome. Outcome classification was performed by two neuroradiologists with more than ten years of experience. Of the 39 cases, 20 were assigned to the positive outcome group and 19 to the negative outcome group. Among negative outcome cases,

first worsening was documented between 3 and 12 months after treatment, most frequently at 6 months.

CNS shape modifications were categorized according to the classification proposed by Larsen et al. [8]. Due to the limited number of cases, the cohort was subdivided only into the first three deformation categories. The resulting groups were defined as follows, with an additional group where no deformation occurs:

- SM0: No deformation of the device
- SM1: Overall flattening of the device
- SM2: Unilateral wing deformation
- SM3: Migration of the device toward the aneurysm dome

Shape-modification categories were evaluated independently of clinical outcome, and multiple assignments were possible if more than one deformation pattern was present in the same case. Thirteen cases showed no deformation, whereas 15, 16, and 10 cases were assigned to SM1, SM2, and SM3, respectively. The corresponding configurations and case distributions are shown in Fig. 1.

Segmentation and ostium extraction

Segmentation of patient-specific vascular structures was performed using the imaging data. A threshold-based segmentation method available in MeVisLab v3.4.1 (MeVis Medical Solutions AG, Bremen, Germany) is used for this purpose, yielding a 3D surface mesh. The anatomical aneurysm dome and ostium were extracted using an in-house–developed script [12], resulting in two separate 3D surface meshes representing the aneurysm head and the ostium (Fig. 2). Here, vessel centerlines are required, which are created using the open-source Vascular Modeling Toolkit (VMTK). Post-processing of the resulting 3D models was carried out using the open-source 3D creation suite Blender v4.2 (Blender Foundation, Amsterdam, Netherlands). During this step, artifacts were manually removed, surface smoothing was applied, and inlet and outlet boundaries were extruded.

Image-based blood flow simulations

The image-based blood flow simulations of the 39 pre-treatment cases were carried out with the finite volume-based solver STAR-CCM+ v17.06 (Siemens PLM Software Inc., Plano, TX) following the guidelines by Berg et al. [13]. From the 3D surface model, an unstructured volumetric mesh was generated using polyhedral cells with a base size of 0.1 mm, along with five layers of prism cells to ensure accurate resolution of near-wall flow.

For the inlet conditions, a representative time-varying inflow curve, captured via Doppler ultrasound, was employed

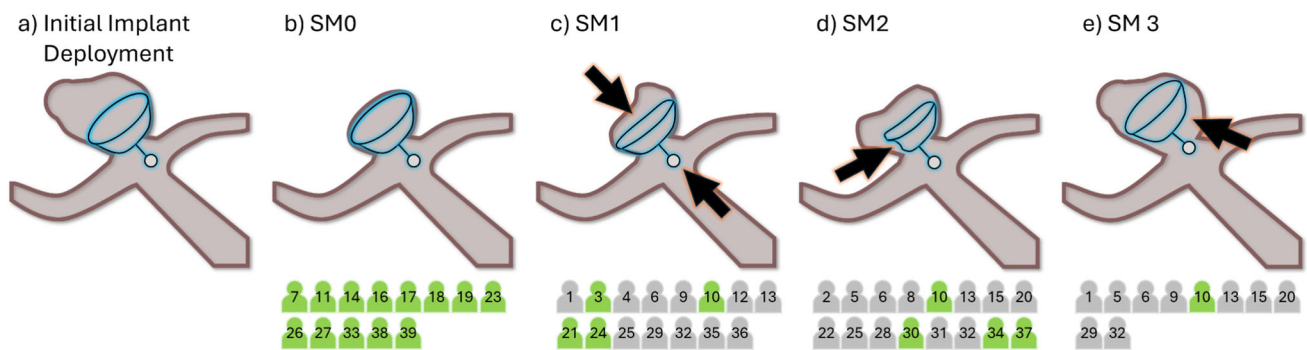


Fig. 1 Classifications of CNS configurations (a) immediately after deployment, (b) at follow-up without deformation, (c–e) the deformation classes SM1–SM3, and the distribution of cases in each class, with positive treatment outcome highlighted in green

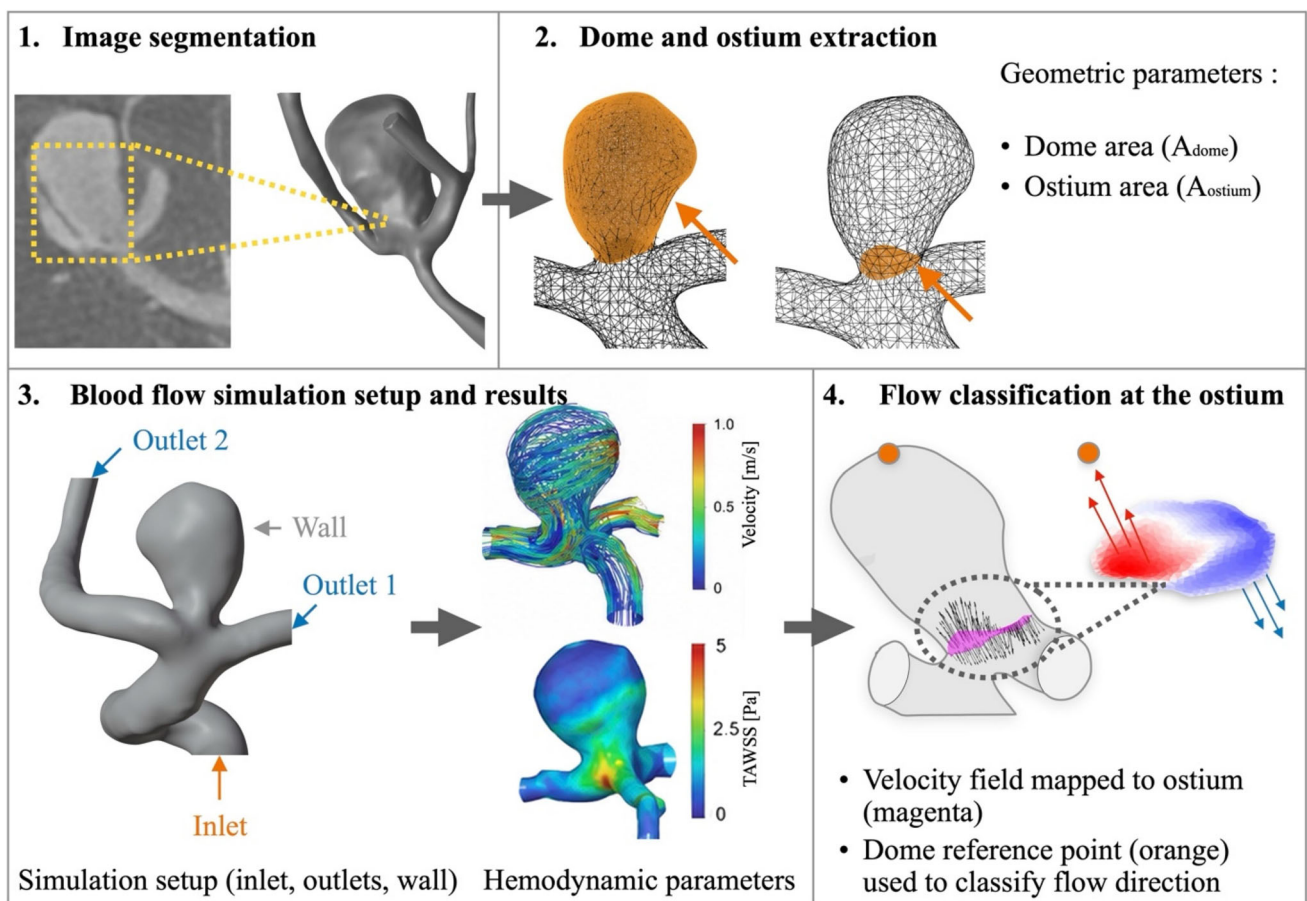


Fig. 2 Overview of the image-processing and simulation workflow. Pre-treatment imaging was used for vascular segmentation (1), aneurysm reconstruction, dome and ostium extraction (2), blood flow simulation, and hemodynamic feature extraction (3). For ostium-flow classification,

velocity vectors were projected onto the ostium surface and classified as inflow (red) or outflow (blue) according to the inward-pointing ostium normal defined by the dome reference point (4)

[14]. To exclude the influence of varying inflow conditions, this waveform was applied uniformly across all simulations.

The outlet boundary condition was defined using a flow-splitting approach based on Murray's law with a power exponent of $n = 2$, taking the respective outlet cross-sectional areas into account. Previous studies have shown that this approach achieves a level of accuracy comparable to that of more advanced flow-splitting techniques [15, 16]. For blood modeling, the Carreau–Yasuda model based on Karimi et al. [17] was used with a constant density of 1055 kg/m^3 . All vessel walls are assumed to be rigid.

Laminar flow conditions were assumed, and a continuity convergence criterion of $1\text{E-}4$ was applied. The governing equations were solved using a segregated flow solver with SIMPLE-type pressure–velocity coupling. Spatial discretization of the convective terms was performed using a second-order scheme, while temporal discretization employed a first-order implicit scheme with a constant time step size of 1 ms. The simulations were initialized using the standard initialization procedure in STAR-CCM+. The velocity field was initially set to zero, and a uniform reference pressure was prescribed throughout the computational domain.

Three cardiac cycles were simulated for each of the 39 configurations. The first two cycles were used for initialization, and the third cycle was used for the actual hemodynamic evaluation to ensure cycle independence.

The following hemodynamic parameters were included in the analysis to generate quantitative input features. Time-averaged values refer to parameters averaged over the last cardiac cycle. The parameter equations are provided in the supplements.

- Time-average wall shear stress intracranial aneurysm (**TAWSS_{IA}**)
Tangential shear stress along the aneurysm wall
- Time-average wall shear stress parent (**TAWSS_{parent}**)
Tangential shear stress along the parent vessel wall
- Time-averaged velocity (**TA_{velo}**)
Time-averaged velocity within the aneurysm sac
- Neck inflow rate (**NIR**)
The net flow rate entering the aneurysm through the ostium.
- Oscillatory Shear Index (**OSI**)
Measure for the change in direction and magnitude of the WSS
- Oscillatory Velocity Index (**OVI**)

Measure for the change in direction and magnitude of the velocity vectors

Ostium-based flow analysis and feature extraction

To enable consistent ostium-based flow analysis, velocity vectors obtained from the CFD simulations were projected onto the extracted ostium surface and decomposed into their local surface-normal component (Fig. 2). Prior to projection, the ostium surface was remeshed using an edge-based iterative splitting approach with a target edge length of 0.2 mm and up to 10 refinement iterations [18], providing a homogeneous spatial resolution for clustering and feature extraction. For consistent orientation across patients, the inward-pointing ostium normal was defined using a dome-based reference direction, determined by the point on the aneurysm dome with the maximum Euclidean distance from the ostium plane. Positive normal velocity was classified as inflow into the aneurysm sac, whereas negative normal velocity was classified as outflow toward the parent vessel.

Spatial heterogeneity of ostium flow was analyzed using density-based spatial clustering (DBSCAN). Clustering was applied to the centroids of the ostium surface elements, weighted by their local normal-flow characteristics. DBSCAN was chosen because it identifies contiguous flow regions without requiring a predefined number of clusters and allows isolated elements to be treated as outliers. Parameters were selected according to the spatial resolution of the remeshed ostium surface, with the neighborhood radius ϵ set to 0.3 mm and the minimum number of faces per cluster set to 10.

Based on the local normal velocity, ostium surface elements were assigned to four flow categories: inflow regions, defined by positive normal velocity above 0.01 m/s; outflow regions, defined by negative normal velocity below -0.01 m/s ; low-flow or stagnation regions, defined by near-zero velocity between -0.01 and 0.01 m/s ; and jet regions, defined by values above the 95th or below the 5th percentile of the normal velocity distribution. These empirically selected thresholds were used consistently for all cases.

From the ostium-flow analysis, peak and percentile-based inflow and outflow velocities, net inflow and outflow rates, relative area fractions of each flow category, flow-balance metrics, and peripheral outflow dominance were extracted. In addition, global geometric descriptors, including ostium surface area and aneurysm dome surface area, were computed. Representative examples of the ostium-flow clustering patterns are shown in Fig. 3. A complete overview of all geometric, hemodynamic, and clustering-derived features is provided in Table 1.

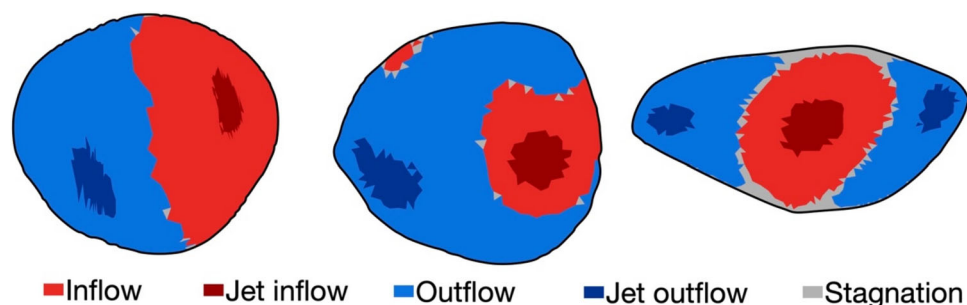


Fig. 3 Representative examples of ostium-based flow clustering in three patients. The 2D ostium projections are viewed from the aneurysm dome toward the ostium plane. The panels illustrate a balanced

flow pattern, pronounced outflow-dominated imbalance, and peripheral outflow/stagnation-dominated flow. Colors indicate DBSCAN-derived inflow, outflow, stagnation, and jet regions

Table 1 Overview of all geometric, hemodynamic, and clustering-derived features

Feature group	Variable name	Description
Geometry	A_{ostium}	Ostium surface area
	A_{dome}	Aneurysm dome surface area
Ostium flow	$\text{inflow}_{\text{peak}}$	Peak inflow velocity
	inflow_{95}	95th percentile of inflow velocity
	$\text{outflow}_{\text{peak}}$	Peak outflow velocity
	outflow_{95}	95th percentile of outflow velocity
	Q_{in}	Net inflow rate
	Q_{out}	Net outflow rate
Ostium-Clustering	$A_{\text{in,rel}}$	Relative inflow area fraction
	$A_{\text{out,rel}}$	Relative outflow area fraction
	$A_{\text{zero,rel}}$	Relative stagnation area fraction
	$A_{\text{jet,rel}}$	Relative jet area fraction
	A_{balance}	Difference between inflow and outflow area fractions
	$\text{periph}Q_{\text{out}}$	Peripheral dominance of outflow

Feature reduction and redundancy control

To reduce redundancy, feature thinning was performed once across the full cohort before endpoint-specific analyses and without using outcome or follow-up labels. Numerical features with high Spearman correlation ($|\rho| \geq 0.90$) were grouped, and the feature with the highest variance was retained from each group. The resulting reduced feature set was used unchanged for all univariate and predictive analyses.

Univariate statistical analysis

Following global feature thinning, univariate statistical analyses were performed to assess associations between individual hemodynamic, geometric, and clustering-derived

features and binary clinical endpoints, including follow-up-based shape modifications (SM1–SM3) and clinical outcome. Clinical outcome and CNS shape modifications were analyzed as separate binary endpoints. For clinical outcome, label 1 indicated positive outcome and label 0 indicated negative outcome. For each shape modification, a separate binary analysis was performed, with label 1 indicating the presence of the respective modification and label 0 indicating its absence. Thus, SM1–SM3 were not treated as mutually exclusive multiclass labels, and the shape modification labels were independent of the clinical outcome label. Feature distributions between groups were compared using the nonparametric Mann–Whitney U test. This test was chosen due to the limited cohort size, the presence of non-normal feature distributions, and potential outliers, making parametric assumptions inappropriate.

In addition to hypothesis testing, the direction and magnitude of group differences were quantified. Directionality was assessed using the difference in medians between groups, indicating whether higher or lower feature values were associated with the endpoint. Effect size was quantified using Cliff's delta, a nonparametric measure describing the probability that a randomly selected value from one group exceeds a value from the other group. To account for multiple comparisons across the feature set, p-values were adjusted using the Benjamini–Hochberg false discovery rate (FDR) procedure [19]. All analyses were conducted independently for each endpoint using the same reduced feature set.

The resulting statistics (p-values, FDR-adjusted q-values, median differences, and effect sizes) were used to identify features with robust univariate associations. In addition, Contour device size was compared between clinical outcome groups as an exploratory sensitivity analysis using the same Mann–Whitney U test and Cliff's delta effect size, but was not included in the main pre-treatment feature set.

Exploratory outcome prediction

To explore whether the extracted pre-treatment features contained information for clinical outcome discrimination, an exploratory machine learning analysis was performed. The input consisted of the globally thinned pre-treatment feature set, including geometric, hemodynamic, and ostium-clustering-derived parameters. The output was the binary clinical outcome label, with label 1 indicating positive outcome and label 0 indicating negative outcome. Outcome discrimination was assessed using a support vector machine (SVM) classifier with a radial basis function kernel. Model performance was evaluated using repeated stratified fivefold cross-validation with 20 repetitions. In each repetition, the cohort was split into five folds while preserving the relative distribution of positive and negative outcome cases as far as possible. For each fold, four folds were used for training and the remaining fold was held out for testing.

To avoid information leakage, feature selection was performed only within the training data of each cross-validation fold. Specifically, feature relevance was estimated using a bagged random forest classifier with out-of-bag permutation importance, and the three highest-ranked features in the respective training fold were selected. The SVM was then trained using only these selected features and evaluated on the corresponding held-out test fold. Input features were standardized within the SVM training procedure. To assess whether the observed performance exceeded chance level, a permutation test was performed by randomly shuffling the outcome labels while preserving the same cross-validation procedure. Because of the limited cohort size, the machine learning analysis was considered exploratory.

Results

Univariate associations with clinical outcome

Immediate post-treatment occlusion showed limited variability, with most cases classified as BOSS 1 (35/39) and no clear descriptive separation between positive and negative outcome groups.

In univariate analyses, aneurysm dome surface area (A_{dome}) showed a significant association with clinical outcome after correction for multiple testing ($q = 0.038$). (Table 2) Patients with a positive outcome exhibited smaller dome areas compared to those with a negative outcome (median difference $-5.0 \times 10^{-5} \text{m}^2$), with a moderate-to-large effect size (Cliff's $\delta \approx -0.57$). Ostium area A_{ostium} demonstrated a similar directional trend toward smaller values in the positive outcome group; however, this association did not remain significant after false discovery rate correction ($q = 0.18$). All remaining hemodynamic and clustering-derived features showed no statistically significant association with outcome following correction ($q > 0.30$).

In an exploratory sensitivity analysis, larger Contour device size was associated with clinical worsening (mean 8.16 mm vs. 6.70 mm; Mann–Whitney U test, $p = 0.011$; Cliff's $\delta \approx 0.45$). However, device size was not included in the main predictive feature set because the primary analysis focused on pre-treatment geometry and hemodynamics.

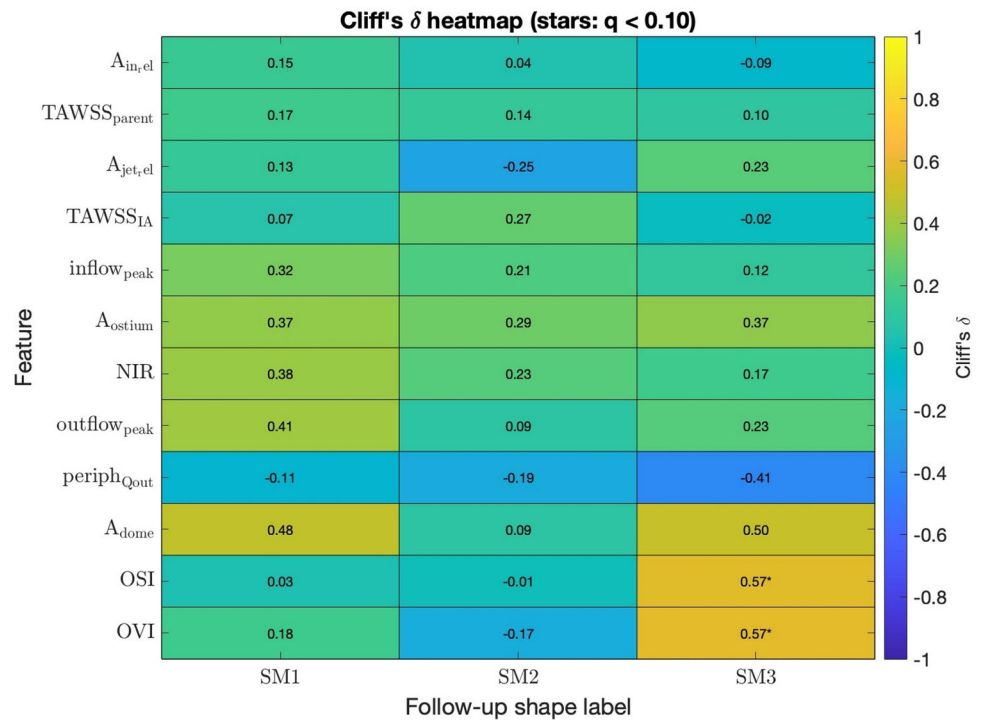
Univariate associations with follow-up shape modifications (SM1–SM3)

An overview of effect sizes across SM1–SM3 is provided in Fig. 4. No feature reached statistical significance after false discovery rate correction for SM1. However, several parameters showed consistent trends. Larger A_{dome} , higher outflow_{peak}, and increased NIR were associated with the presence of SM1, each exhibiting moderate effect sizes (Cliff's $\delta \approx 0.38$ – 0.48).

No statistically significant associations were identified between the investigated features and SM2 after false discovery rate correction. Nevertheless, several parameters exhibited modest but consistent effect sizes. The largest effects were observed for TAWSS_{IA} (Cliff's $\delta \approx 0.27$), A_{ostium} ($\delta \approx 0.29$), and $A_{\text{jet,rel}}$.

For SM3, several features showed strong univariate associations. OVI and OSI demonstrated the largest effect sizes (Cliff's $\delta \approx 0.57$ and 0.56 , respectively), with both parameters being higher in patients exhibiting SM3. Although these associations narrowly missed statistical significance after false discovery rate correction ($q = 0.066$ for both). Both parameters fell below the exploratory threshold ($q < 0.10$) and exhibited large effect sizes, indicating a substantial separation between groups.

Fig. 4 Cliff's delta heatmap for follow-up shape modifications (SM1–SM3). Colors indicate the direction and magnitude of the effect size, with positive values indicating higher feature values in cases with the respective shape modification and negative values indicating lower feature values. Asterisks denote features with $q < 0.10$ after false discovery rate correction



Exploratory prediction of clinical outcome

In exploratory predictive analyses with feature selection performed within each training fold, the SVM classifier achieved a mean AUC of 0.57 across 20 repetitions of stratified fivefold cross-validation (95% CI: 0.41–0.71). Model performance exceeded the permutation baseline (mean AUC = 0.47), but the difference did not reach statistical significance (permutation $p = 0.20$). The most frequently selected features across cross-validation folds were A_{dome} , $A_{out,rel}$, $outflow_{peak}$, and A_{ostium} which were consistent with the strongest univariate associations.

Discussion

This study examined whether pre-treatment geometric and hemodynamic characteristics of intracranial aneurysms are associated with clinical outcome and with specific post-treatment shape modifications of the CNS. Univariate analyses identified aneurysm geometry as the strongest determinant of clinical outcome. Smaller aneurysm dome and ostium areas were associated with positive outcome, likely enabling more effective flow disruption and subsequent thrombus formation. This observation is consistent with prior reports describing ostium shrinkage as part of the healing response after CNS deployment, suggesting that smaller ostia

may facilitate more stable device–aneurysm interaction and occlusion [20]. Hemodynamic parameters showed weaker but directionally consistent trends, with lower NIR and reduced peak outflow velocities in positive outcome cases, indicating that both geometric confinement and reduced ostium-level flow exchange may contribute to treatment success.

Analysis of post-treatment CNS shape modifications provided further mechanistic insight. Device flattening (SM1) and unilateral wing deformation (SM2) were predominantly associated with negative outcome and showed moderate associations with larger neck geometries and asymmetric flow exposure. In contrast, device migration toward the aneurysm dome (SM3) exhibited the strongest associations, characterized by elevated oscillatory flow metrics, larger dome areas, and decreased peripheral outflow dominance. These findings suggest that unstable and oscillatory flow conditions at the aneurysm neck may promote device displacement and compromise long-term occlusion.

Outcome prediction is influenced by morphology, hemodynamics, and device deformation. To our knowledge, this is the first study to integrate simulation-derived features into ML-based outcome prediction for the CNS. For more established therapies such as flow diverters, several studies have already explored machine-learning-based outcome prediction [21, 22]. Notably, Paliwal et al. [23] applied a similar approach combining virtual stenting with ML and reported

Table 2 Strongest univariate associations between pre-treatment features and clinical outcome

Feature	<i>q</i> -value	Δ Median (1–0)	Cliff's δ
A_{dome}	0.038	– 5.0e – 05	– 0.57
A_{ostium}	0.18	– 3.0e – 06	– 0.43
NIR	0.308	– 0.38	– 0.35
outflow _{peak}	0.498	– 0.03	– 0.28

strong predictive performance, achieving outcome prediction accuracies of up to 90%. These results provide strong motivation to further expand the present study. Extending this approach could support clinical decision-making in the future, as the analysis of pre-treatment features holds substantial value for enabling more precise, patient-specific treatment strategies.

This study has several limitations. Firstly, the cohort size was small, resulting in limited subgroup sizes for specific shape modifications and limited machine learning performance. Larger multicenter cohorts are required to validate the observed associations and enable more robust predictive modeling. Secondly, outcome classification was based on all available follow-up imaging rather than on a fixed standardized time point; therefore, variable follow-up duration may have introduced temporal heterogeneity, and late recurrence or deformation may have been missed in cases with shorter follow-up. Thirdly, the blood flow simulations relied on simplifying assumptions, including rigid vessel walls and uniform, non-patient-specific inflow conditions. Although these assumptions are consistent with established practice in comparable studies, they may affect absolute hemodynamic values [13]. Finally, device size was evaluated only in an exploratory sensitivity analysis and was not included as an explicit predictor. Because device size is closely linked to aneurysm geometry, it cannot be interpreted as an independent device-related effect. Future studies should incorporate dedicated size-matching metrics, such as contour size/neck and contour size/dome ratios [6, 8, 24].

The present findings suggest that pre-operative geometric and hemodynamic characteristics are linked not only to clinical outcome but also to specific CNS shape modifications observed at follow-up. This highlights the importance of considering both flow conditions and device–aneurysm interaction when planning treatment.

Conclusion

This study shows that pre-treatment aneurysm geometry and hemodynamics are associated with clinical outcome and follow-up CNS shape modifications. Smaller dome and

ostium areas were linked to favorable outcome, whereas specific deformation patterns were associated with distinct hemodynamic conditions, particularly oscillatory ostium-level flow. These findings suggest that simulation-derived pre-treatment features can improve the mechanistic understanding of CNS treatment failure and may support future patient-specific treatment planning after validation in larger cohorts.

Supplementary Information The online version contains supplementary material available at <https://doi.org/10.1007/s11548-026-03777-y>.

Funding Open Access funding enabled and organized by Projekt DEAL. This research was supported by the IDIR-Project (Digital Implant Research), a cooperation financed by Kiel University, University Hospital Schleswig–Holstein and Helmholtz Zentrum Hereon. This study was partly funded by the Federal Ministry of Research, Technology and Space within the Forschungscampus STIMULATE (grant number 13GW0835A), the German Research Foundation (grant number 548907942), and the European Regional Development Fund (ZS/2023/12/182010).

Data availability Processed data and code is available upon request from the corresponding author.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

Ethical approval All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki Declaration and its later amendments or comparable ethical standards.

Informed consent Informed consent was obtained from all individual participants included in the study.

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