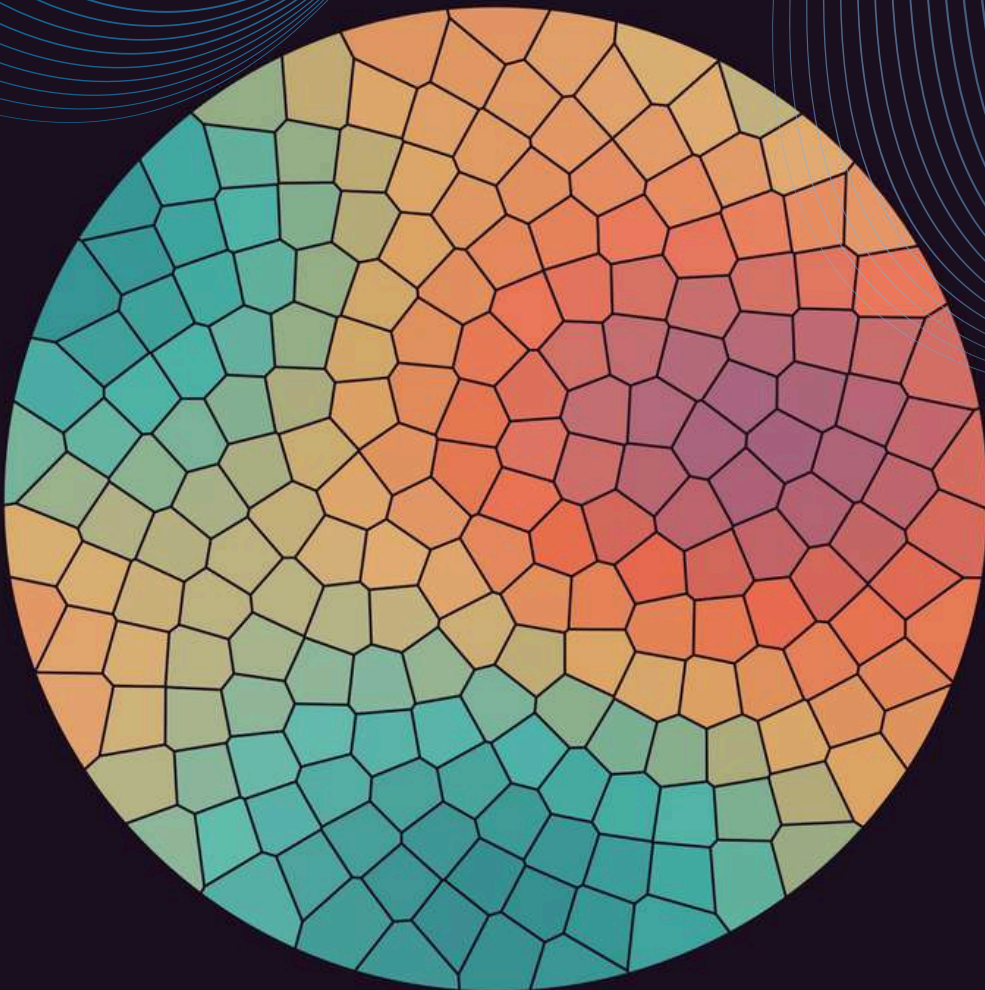




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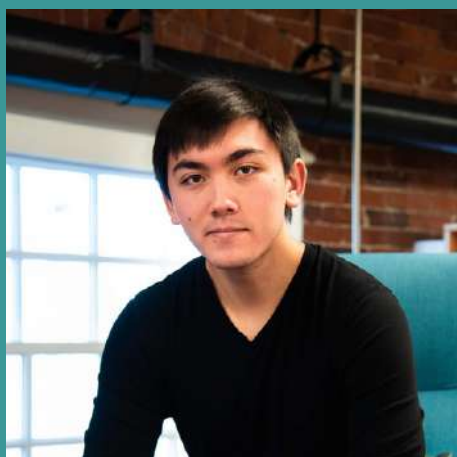
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WINNER OF THE 2025- 2026 BEST UNDERGRADUATE PAPER AWARD

*More Than Just Crowd Noise - Factors That Drive
Home Advantage in the English Premier League*

More Than Just Crowd Noise

*Examining the Factors That Drive Home Advantage in
the English Premier League*

Abstract:

Using regression analysis of 380 matches from the 2018–2019 English Premier League season, we examine factors associated with home goal difference. Attendance, shots, possession, and expected goals were significant predictors. The model explained 28% of the variation, suggesting that both crowd support and team performance matter for home success.

I. Introduction

More than 14 million fans attended matches during the English Premier League (EPL) 2018-2019 season, making it one of the most-watched sports competitions (ESPN, 2019). This massive fanbase highlights the long-discussed concept of home-field advantage, where teams are believed to perform better when playing in their own stadium. Although often associated with fan pride and crowd energy, the exact causes of home advantage remain debated.

Research has shown consistent evidence of home advantage in soccer. Pollard (2006) found that home teams win more points across leagues on average, while Page (2007) suggested that crowd size may play a major role in influencing both players and referees. More recent work by Bandara et al. (2024) showed the usefulness of advanced statistics like expected goals (xG) in predicting outcomes. Still, little is known about how multiple factors influence home advantage. This study examines how contextual factors such as crowd size and referee decisions, along with performance measures including shots, possession, and expected goals, work together to explain differences in home goal margins in the Premier League.

Understanding the drivers of home advantage has a broad value for the sports industry. Betting markets, television broadcasters, and even stadium management depend on accurate forecasts of match outcomes. Identifying reliable predictors of home success deepens academic understanding and informs commercial decision-making.

This project uses EPL match data from the 2018–2019 season to test whether attendance, shots difference, fouls difference, red cards difference, possession difference, and expected goals difference predict home goal difference. By combining both contextual and performance-based variables, this analysis aims to understand what drives home success in the Premier League.

II. Methods

Motivated by previous evidence of home-field advantage, we leverage data from the 2018–2019 EPL to examine such relationships through the observation of match-level data. The dataset, obtained from FootyStats.org, compiles official match records into a single table with distinct home and away variables for each statistic. FootyStats.org was the chosen source because the dataset included contextual data like date, referee, and attendance, along with performance-based metrics like goals, shots, fouls, possession, and xG per every league match (FootyStats, 2019).

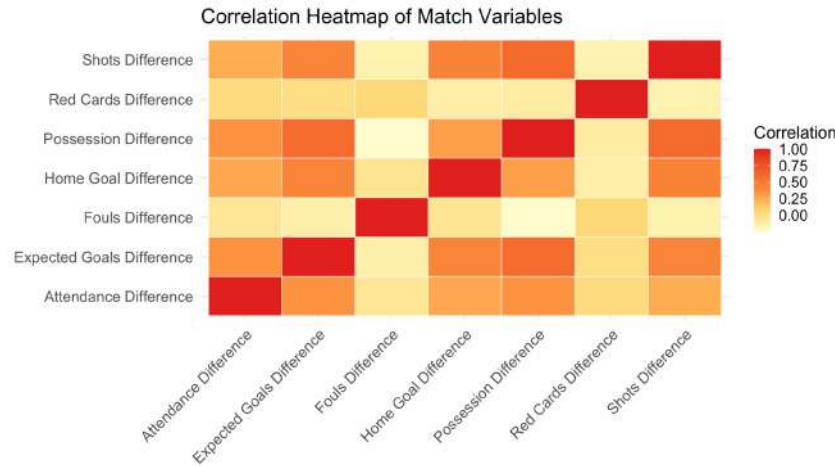
The data comprised 380 completed EPL matches, corresponding to one observation per match. Each observation represents a single fixture between two teams, with separate fields for home and away performance. Stadium, city, and kickoff time columns in the file verified the competition and the window. No primary data collection was conducted; instead, publicly recorded data were compiled by the source to facilitate analysis and fan studies (FootyStats, 2019).

The response variable was defined as home goal difference, calculated as home goals minus away goals. Aligning with the research question, six predictors were constructed as home-minus-away differences: attendance, shots, fouls, red cards, possession, and pre-match expected goals (xG). Variables unrelated to the study's objectives, such as referee name, stadium, city, and kickoff time, were excluded from the analysis to focus on performance and contextual factors most relevant to home advantage.

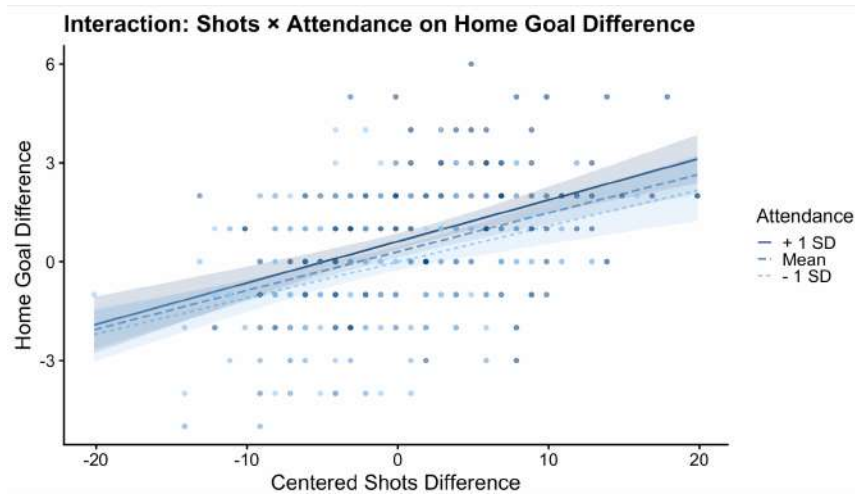
Some data collection details were taken into account. Variation in provider approaches (e.g., how possession time is counted), reporting practices for attendance, and the xG modeling assumptions can be noisemakers; variability between referees can be another source of card count variability. No additional adjustments beyond the cleaning steps above were applied at this stage, but these potential inconsistencies and data source limitations will be considered when interpreting the regression results.

III. Results

The modeling process began by examining relationships among predictors to check for multicollinearity. The correlation heatmap (Figure 1) showed no strong relationships among variables, indicating that attendance, shots, fouls, red cards, possession, and expected goals (xG) each captured distinct aspects of match performance. Because no interaction effects were observed in exploratory plots (Figure 2), only main effects were included in the model.



(Figure 1)

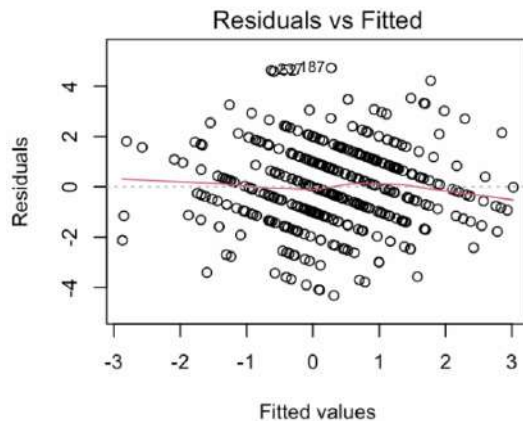


(Figure 2)

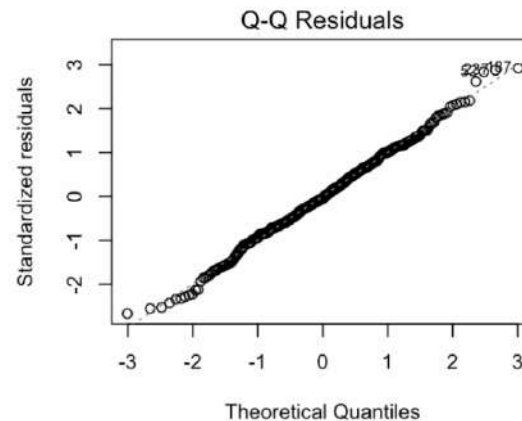
An information-based variable selection method using the Akaike Information Criterion (AIC) was then used to simplify the model. The fouls variable was removed, resulting in a final model that included attendance difference, shots difference, red cards difference, possession difference, and xG difference.

The regression explained about 27 percent of the variation in home goal difference ($R^2 = 0.28$). Attendance difference ($p = 0.0166$), shots difference ($p < 0.001$), possession difference ($p = 0.0152$), and xG difference ($p < 0.001$) were significant predictors. Each had a positive relationship with home goal difference, suggesting that greater attendance, more shots, higher possession, and stronger xG all increased a team's goal advantage at home. Red cards difference had a negative but only marginally significant effect ($p = 0.0527$), indicating that receiving more red cards slightly reduced goal margins.

Model evaluation confirmed that linear regression assumptions were met (as shown in Figures 3 and 4). Residuals were randomly distributed, normally shaped, and showed constant variance, supporting the reliability of the model results.



(Figure 3)



(Figure 4)

IV. Discussion

The analysis provided a concrete understanding of the factors that contributed to home advantage in the Premier League. The final model showed that attendance, shots, possession, and xG were all significant predictors of home goal difference, showing how both contextual support and offensive performance played important roles in match outcomes. Larger crowds and stronger home results were associated, emphasizing that crowd presence influences match dynamics. Offensive activity was measured through shot creation and expected goals, and also had strong positive relationships with home goal difference. This suggests that teams that generated better chances and more attempts tended to achieve larger margins on their home ground.

One of the more interesting findings involved possession. The model revealed a small but statistically significant negative relationship between possession difference and home goal difference. Although possession is often viewed as positive and an indicator of control, this result likely reflected in-game effects rather than performance decline. Teams that fall behind sometimes dominate the ball while searching for an equalizer, while teams holding a lead often give up possession and focus on protecting the score. Therefore, the negative coefficient aligns with common match patterns.

The effect of red cards was negative, as expected, though largely insignificant. Because red cards are rare and often occur late in matches, their impact on total goal difference can be difficult to detect in a single-season dataset. Still, the direction of the effect suggested that discipline mattered and could play a role in shifting match outcomes in more extreme cases.

The model explained approximately 28 percent of the variation in home goal difference, indicating moderate predictive power. This reflects the usefulness and limitations of statistics in predicting future outcomes. Home advantage is a complex multi-factor variable influenced by tactical choices, team quality, psychological factors, travel patterns, and other variables that were not included in the available data. Incorporating team-level metrics such as expected standings, player availability, or betting odds would likely capture a larger share of variation in future analyses.

There are several limitations worth noting. Attendance was measured as total crowd count rather than capacity percentage, which meant the data reflected size but not intensity. This may have understated the advantage experienced by teams with smaller but full stadiums. The expected goals measure relied on

underlying statistical models, and differences in assumptions could introduce noise in how expectations were evaluated. Using only one season of data also restricted the ability to identify patterns.

Overall, the study showed that both the environment and how teams played were key roles in determining home success in the Premier League. Crowd presence, shot creation, and expected goals were all influential. While home advantage remains a complex phenomenon, the results demonstrate how statistics can highlight the key factors that shape it. Future research could extend to multiple seasons or incorporate new variables to build a better understanding of why teams perform better at home.

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KATHLEEN QUARDOKUS FISHER

WINNER OF THE 2025-2026 BEST GRADUATE PAPER AWARD

*Virtual Reality Field Trip to Western
Ireland Coastal Boulder Deposits*

Virtual Reality Field Trip to Western Ireland Coastal Boulder Deposits

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Abstract. This work presents *The Inishmaan VFT: Lifecycle of a Boulder*, a data-driven virtual field trip that integrates high-resolution geomorphic surveys, 3D LiDAR boulder scans, and hydrodynamic storm simulations from Inishmaan, Ireland into an immersive Unity environment. To maximize educational accessibility, the high-fidelity VR experience is paired with a cross-platform, browser-accessible 360° ThingLink interface. The resulting module provides a transferable framework for inclusive, place-based instruction that enables students to investigate coastal process-response dynamics and hazard management without geographic or financial barriers.

1. Background

Field-based instruction is central to college-level geoscience and geography education [1–7], and its efficacy is often rooted in field and place-based learning (PBL). The PBL pedagogical approach leverages the unique geological, cultural, and environmental identity of a location to foster a deeper sense of stewardship and cognitive connection [2–3,5,7]. However, the remote or rugged nature of geological sites often introduces barriers related to cost and accessibility [8]. Virtual reality (VR) offers a pathway to preserve these place-based strengths. By creating an immersive field site of Inishmaan, Ireland, we provide students with a sense of place standard textbook examples may lack, allowing for students to build a connection to a landscape.

It has been argued that Inishmaan, Ireland, represents one of the best natural laboratories for coastal boulder deposits (CBD) [9–10,13–14]. CBDs are essential sedimentological proxies because they can be used to reconstruct past tsunami and storm effects on rocky coastlines, vital for coastal hazard management [9]. Beyond research, CBDs are effective tools for teaching students how to interpret physical proxies for high-energy events [e.g., 10, where method, 12, was taught]. On Inishmaan, recent findings demonstrated that tidal range coincidence with storm waves is a first-order parameter in storm-driven CBD transport [10, 12–14]. This was particularly evident during Storm Fergus on December 10, 2023 [13]. Thus, this virtual field trip (VFT) presents an opportunity to teach both CBD geomorphology and hydrodynamics through a focused study of a western site, chosen due to its rich dataset.

2. Central Focus

This study presents the development of a college-level VFT titled, “The Inishmaan VFT: Lifecycle of a Boulder”. This work makes three primary contributions: (i) the development of a research-grade, data-driven VFT that integrates real coastal geomorphology datasets; (ii) a transferable workflow for visualizing spatial field data using VR to support inclusive instruction; and (iii) a process-based design that enables students to compare environmental forcing scenarios and evaluate geomorphic response using real storm observations.

3. Intellectual Merit

We introduce a data-driven virtual field environment that integrates real coastal geomorphic measurements with immersive visualization and interactive annotation to support research, teaching, and accessibility in rocky-coast geomorphology. Specifically, the objectives of this work are to:

- (1) integrate spatially and temporally resolved field measurements from Inishmaan Site 3 (western side of Inishmaan) during Storm Fergus into a data-driven virtual reality environment;
- (2) implement scenario-based exploration to examine how combinations of tidal stage and meteorological forcing influence coastal processes, including the conditions under which coastal boulder transport may or may not occur; and
- (3) student observation, interpretation, and synthesis by augmenting outcomes from the VR experience with those from a less interactive but still immersive visualization.

3.1 Dataset Acquisition and Processing

In 2023, an uncrewed aerial survey (UAS) was processed using the Structure-from-Motion (SfM) method into a 10 cm resolution digital elevation model (DEM) and an orthomosaic using Pix4D software [13, 16, 20]. Study boulders were scanned using iPhone LiDAR and post-processed in Blender into watertight 3D models [12, 17, 18]. Onshore pressure sensors during Storm Fergus logged data which we converted into apparent onshore depths to determine CBD submergence during transport events [11]. While onshore run-up was not directly observed, these depths and relative

submergence ratios were informative. Additional 360° photos of the site were collected in Spring 2025 to document post-winter storm positions using best research field practices and research support by NHERI RAPID [16-17].

3.2 VR Environment Construction

The environment was constructed in Unity [23] using the UAS-derived DEM as the terrain base and the orthomosaic as a high-resolution texture layer, using method from [18]. 3D LiDAR-scanned boulders were placed in their pre-Storm Fergus positions [12]. Boulders were animated to move along pathways following field-verified abrasion trails, with movement modes (e.g., sliding vs. rolling) informed by accelerometer orientation logs and field surveys [13]. To avoid speculative assumptions regarding exact transport timing, a “summary transport wave” approach was utilized to summarize the transport window [13]. Apparent onshore water levels, guided by pressure sensors and tide gauges [14], were overlaid with a computational fluid dynamic (CFD) simulation in Blender [21-22] to render the run-up, bore, and drawdown on the supratidal platform. Realistic environmental assets, including rain and spatialized audio of crashing waves, were added to enhance immersion.

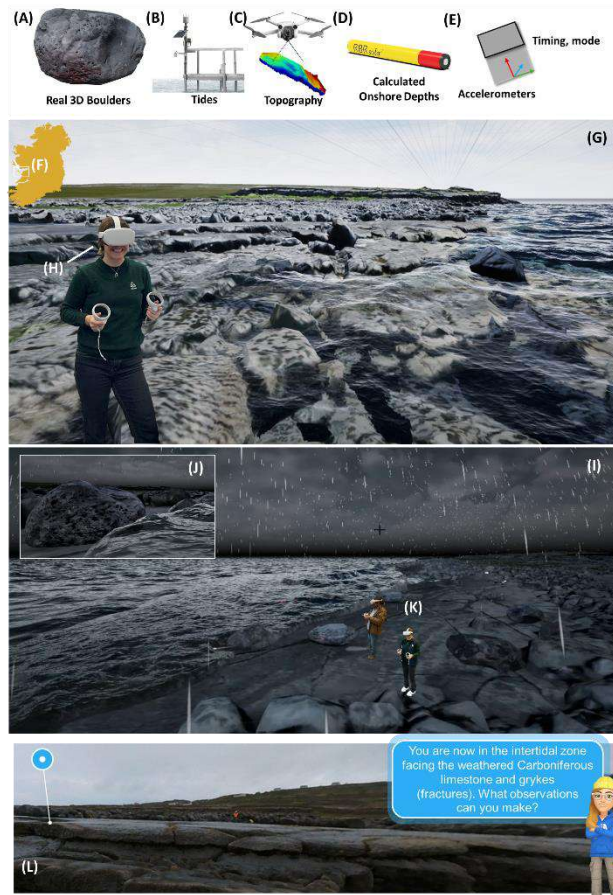


Figure 1. (A–E) Field datasets used to construct the virtual environment, including high-resolution terrain and boulder models. (F) Location of the study site in western Ireland. (G, I) Low-tide/sunny and high-tide/stormy environmental scenarios available to students. (H, K) Example user interactions within the VR environment. (J) Boulder submergence state used to illustrate transport-relevant forcing conditions. (L) Supplementary annotated 360° imagery delivered using ThingLink with guided prompts.

A critical component of this module’s accessibility is the integration of ThingLink [15]. While the Unity VR environment offers high-fidelity immersion, it requires specific hardware. ThingLink serves as a low-bandwidth, cross-platform alternative accessible via any web browser. We utilized 360° photos from a Spring 2025 survey and populated them with interactive hotspots linking to the research-grade datasets. This allows students to verify boulder final positions and observe physical platform features, bridging the gap between simulated transport and real-world evidence.

4. Broader Impacts

We developed a data-driven VR field module that demonstrates a transferable framework for integrating research-grade field data [13-14] into immersive learning environments. By prioritizing a place-based motivator, the VFT ensures a targeted exploration of the Inishmaan’s CBDs. This immersion encourages students to view geomorphology and hydrodynamics through the lens of a specific, dynamic case study [6]. Furthermore, although designed for immersive virtual reality, the VFT can be accessed through standard desktop or laptop computers without specialized hardware. The ThingLink platform is widely available on desktop or laptop computers, and future versions will have interactive annotation layers to further enable engagement with field measurements and note taking. This tiered access approach lowers barriers related to cost, mobility, safety, and geographic location, supporting inclusive participation in field-based learning and research. Finally, beyond technical skills, the module illustrates the iterative nature of scientific progress, demonstrating how new findings regarding tidal influence [13] change established perspectives, and we can use PBL to achieve those objectives. Future work involves a planned pilot with students to evaluate place-based connections and professional judgment through pre- and post-module assessments and WebGL environment development of the VR environment.

Data Accessibility Statement.

The high-resolution DSM datasets and storm season surveys supporting this work are available via Zenodo [24] and the 360° imagery deposited within DesignSafe-CI [25]. ThingLink environment accessible at [26]. An example of the VR environment available from [27], which demonstrates the storm and high tide setting.

Acknowledgments. Field data collection: Bourke, Greaney, Reisch, and Spero. Funding: Naughton Foundation (Bourke), College of Engineering Undergraduate Grant (Reisch), National Science Foundation (NSF) GRFP (Spero), & GLOBES Mini-Grant (Spero). Field Permissions (Bourke). Data was collected in part using equipment provided by the NSF as part of the RAPID Facility. A component of the NHERI, Award No. CMMI: 2130997. Any opinions, findings, conclusions, and recommendations presented in this paper are those of the authors and do not necessarily reflect the views of the NSF. This work was presented at the American Geophysical Union Annual Meeting 2025.

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HARIHARA MAHARANA

WINNER OF THE 2025- 2026 BEST FIGURE AWARD

*Hemodynamic Predictors of Abdominal Aortic
Aneurysm Rupture Risk*

Hemodynamic Predictors of Abdominal Aortic Aneurysm Rupture Risk

Harihara Maharna*

Abstract

Abdominal aortic aneurysm (AAA) rupture is fatal in most cases, yet the main clinical criterion for elective repair, a maximum diameter above 5.5 cm, does not reliably identify which aneurysms will rupture. Wall shear stress (WSS)-derived parameters computed from computational fluid dynamics (CFD) simulations have been proposed as complementary indicators of rupture risk. In this study, blood flow was simulated in an AAA model from the SimVascular repository and in a virtually repaired version of the same geometry, and four WSS-derived parameters were computed: time-averaged WSS (TAWSS), oscillatory shear index (OSI), endothelial cell activation potential (ECAP), and relative residence time (RRT). The two models were compared to observe how these parameters respond to the removal of the aneurysmal deformation. Interpreted alongside published studies, the results illustrate how each parameter captures a different aspect of disturbed flow and why no single parameter is sufficient to locate rupture-prone regions. This study will be useful for understanding the physical representation of WSS-related parameters in cardiovascular flows and how they can be calculated practically for AAA investigations.

Keywords: Abdominal aortic aneurysm; computational fluid dynamics; wall shear stress; hemodynamics; rupture risk

Introduction: An abdominal aortic aneurysm (AAA) is a life-threatening cardiovascular condition characterized by the localized enlargement of the abdominal aorta, exceeding 50% of its normal diameter. AAA rupture carries a mortality rate of 70-90%. Approximately 15,000 deaths annually in the United States are attributed to AAA [15, 8]. Current clinical practice relies on aneurysm diameter (> 5.5 cm) as the primary criterion for surgical intervention, but this approach has limitations [11]. Small AAAs can rupture unexpectedly, while larger ones may remain stable, highlighting the need for more accurate rupture risk assessment methods.

Hemodynamics, particularly wall shear stress (WSS)-derived parameters such as time-averaged WSS (TAWSS), oscillatory shear index (OSI), endothelial cell activation potential (ECAP), and relative residence time (RRT), offer promising alternatives. Computational fluid dynamics (CFD) simulations can provide patient-specific insights into the mechanical forces on the aneurysm wall, and previous studies have shown that abnormal WSS patterns correlate with aneurysm progression

[16, 19]. However, integrating these parameters into clinical practice remains a challenge. This study aims to address this gap by investigating WSS-derived parameters in both diseased and virtually repaired AAA models to examine how these parameters could contribute to rupture risk assessment.

Methods: An abdominal aortic aneurysm (AAA) model was selected from the SimVascular repository (Figure 1), with a finite element mesh generated using TetGen [17]. Blood flow was modeled as an incompressible Newtonian fluid (density $= 1.06$ g/cm³ and viscosity $= 0.04$ dyn-s/cm²) governed by the Navier-Stokes equations, and boundary conditions were applied using a lumped parameter network model. A virtually repaired model (Figure 6) was created by removing the aneurysmal deformation while preserving the inlet and outlet anatomy. Both models were simulated under identical flow conditions to isolate geometric effects.

The WSS-derived parameters were calculated as follows [10]: Time-averaged WSS (TAWSS) was computed as

$$\text{TAWSS} = \frac{1}{T} \int_0^T |\tau_w| dt, \quad (1)$$

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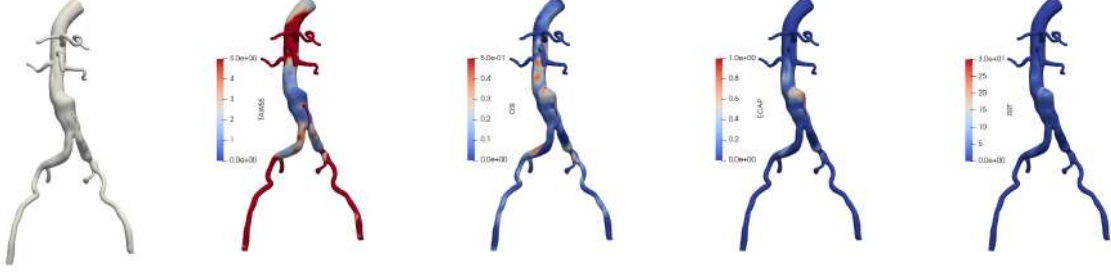


Figure 1: AAA model Figure 2: TAWSS of the original model Figure 3: OSI of the original model Figure 4: ECAP of the original model Figure 5: RRT of the original model

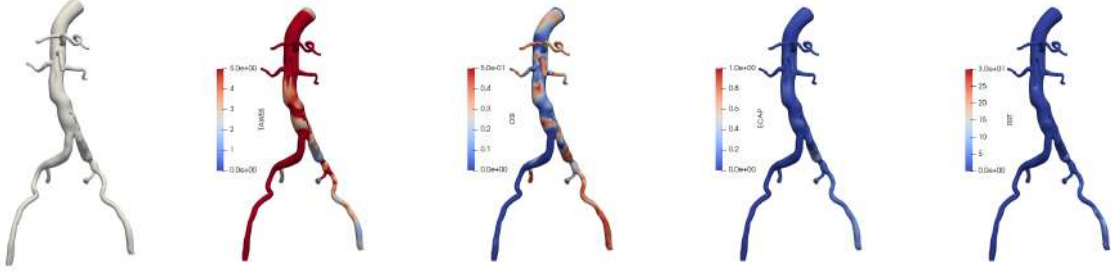


Figure 6: Repaired AAA model Figure 7: Repaired TAWSS Figure 8: Repaired OSI Figure 9: Repaired ECAP Figure 10: Repaired RRT

where τ_w is the instantaneous WSS vector and T is the cardiac cycle duration. The Oscillatory Shear Index (OSI) was calculated as

$$OSI = \frac{1}{2} \left(1 - \frac{\left| \int_0^T \tau_w dt \right|}{\int_0^T |\tau_w| dt} \right), \quad (2)$$

quantifying the directional changes of WSS during the cardiac cycle. The Endothelial Cell Activation Potential (ECAP) was computed as

$$ECAP = \frac{OSI}{TAWSS}, \quad (3)$$

indicating thrombogenic susceptibility, and the Relative Residence Time (RRT) was calculated as

$$RRT = [(1 - 2 \times OSI) \times TAWSS]^{-1}, \quad (4)$$

which estimates the blood residence time near the vessel wall.

Results and Discussion: The hemodynamic parameters analyzed in this study, Time-Averaged Wall Shear Stress (TAWSS), Oscillatory Shear Index (OSI), Endothelial Cell Activation Potential (ECAP), and Relative Residence Time (RRT), provide critical insights into the potential rupture zones of abdominal aortic aneurysms (AAA). As shown in Figure 2 and Figure 7,

TAWSS plays a key role in identifying critical regions in the aneurysm, but it is not sufficient on its own to predict rupture sites. The presence of intraluminal thrombus (ILT) and other factors, such as the thickness of the ILT, must be considered when assessing rupture risk [19]. The OSI values, depicted in Figure 3 and Figure 8, highlight the regions with oscillatory shear stress, which are associated with endothelial dysfunction and thrombus formation. The combination of high OSI and low TAWSS has been associated with aneurysm growth and rupture [3, 20, 18], although its relationship with thrombus deposition varies across studies [1, 13].

The ECAP metric, shown in Figure 4 and Figure 9, further refines the understanding of rupture risk by identifying areas with high endothelial cell activation, which correlates with regions susceptible to thrombus formation. The ECAP index, calculated from the ratio of OSI to TAWSS, is particularly useful in identifying regions exposed to both high OSI and low TAWSS, which are more prone to thrombogenesis [5]. As illustrated in Figure 5 and Figure 10, RRT is inversely related to TAWSS and helps identify disturbed flow patterns that correlate with increased thrombus formation [7]. RRT's relationship with TAWSS and OSI further underscores its potential as a unified indicator

for predicting regions of low and oscillatory shear stress, which are associated with increased rupture risk in AAAs [18].

In summary, while TAWSS provides valuable information regarding wall shear stress distribution, combining it with OSI, ECAP, and RRT enhances the ability to predict rupture-prone areas in AAAs. Combining these metrics may therefore offer a more comprehensive picture of rupture risk than any single metric, although this still needs to be tested against clinical outcomes.

Broader Impacts, Limitations, and Conclusion:

The implications of this work extend beyond its technical contributions to cardiovascular modeling. The groups most likely to benefit are patients whose rupture risk is poorly described by diameter alone. In the United States, one-time ultrasound screening is recommended for men aged 65 to 75 who have ever smoked [6], and the small aneurysms found this way are typically monitored until they reach the 5.5 cm repair threshold, even though some rupture below it [12]. Women are a second group: they are not routinely screened under the same recommendations [6], and women with aneurysms of 5.0 to 5.9 cm have been reported to have about four times the rupture risk of men with aneurysms of the same size [4]. If validated in larger patient cohorts, WSS-derived parameters could complement diameter during surveillance by flagging aneurysms with disturbed flow for closer follow-up. Access is an equally important consideration. Patient-specific CFD requires CT imaging, segmentation expertise, and computing resources, and practicality, accessibility, and validation remain barriers to its clinical use [9, 14]. Open-source tools such as SimVascular, used in this study, remove software licensing costs, but faster and more automated workflows would be needed for such analyses to be available outside specialized research centers.

This study was based on a single representative AAA model from the SimVascular repository, which allowed a direct comparison with its virtually repaired geometry under identical flow conditions. Blood was modeled as a Newtonian fluid, which is a common assumption for large arteries such as the aorta [10, 19], although non-Newtonian models have been shown to affect the vortical flow structures in AAAs [2]. Extending this analysis to a larger number of patient-specific AAA models, and to non-Newtonian blood models, would help generalize these findings. On a broader scale, these advancements could foster interdisciplinary collaborations between engineering, medicine, and

healthcare policy, encouraging more integrated approaches to disease management and promoting a deeper understanding of cardiovascular health.

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CONTRIBUTED ARTICLES

Deploying Anchored Ensembles for Deep Operator Network Surrogate Models

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Abstract: Deep neural networks are deterministic without fundamentally altering their architecture; however, they are employed in a range of disciplines that increasingly ask for decision-making, judgment, and other complex tasks with no definite answer. This means that when a neural network is given identical inputs, it will yield identical outputs without variation. Because complex tasks require answers to be justified, models must be able to indicate what degree of certainty can be assigned to their answer, and most statistical methods require variation to estimate uncertainty. Bayesian neural networks effectively utilize statistical priors to estimate uncertainty, but they are computationally expensive. Monte Carlo dropout randomly removes parameters from the network to synthesize variability; however, this introduces noise which is not informed by explicit priors. This article examines anchored ensembles, which introduce variability informed by priors without incurring the prohibitive expense of Bayesian neural networks. We apply them to deep operator networks trained on the difference between low-fidelity physics simulations and high-fidelity simulations, so that predictions of safety and structural tolerance can be qualified.

Background: Developing full-scale models of physical systems can yield predictions with high fidelity, but these often come at great computational expense. Further, relying on machine learning (ML) models to fully replace these models as surrogates completely abandon any known physics. In lieu of full replacement, ML models such as deep operator networks can also be used to capture the discrepancy, or residual, between a computationally efficient low-fidelity representation and the original high-fidelity model (De and Brewick, 2024). However, these predictions are inherently deterministic, which leads to another issue: ML methods can be overconfident in their predictions and output.

Within rigorous engineering applications this overconfidence can manifest as an absence of uncertainty, which diminishes the utility of both an AI model and its predictions. Uncertainty can be accounted for through techniques such as Monte Carlo dropout or through approximate Bayesian methods (Ghorbanian et. al, 2025); however, because of their high parameter count, quantifying uncertainty through probability distributions of network weights, as in Bayesian neural networks, is far too computationally expensive (Pearce et. al, 2020). Furthermore, neural networks risk experiencing uncertainty collapse when more than one is trained on a dataset (Kirsch, 2024). Thus, simply training an ensemble of models and computing population statistics for confidence intervals typically yields an overconfident, narrow prediction interval because the network realizations lack sufficient diversity. To improve uncertainty quantification within ML techniques, this study explores using anchored ensemble methods to quantify the uncertainty within deep operator networks that are subsequently used to conduct physics-based simulations. Specifically, the anchored ensembles yield confidence intervals and prediction envelopes that can replace standard deterministic predictions.

Central Focus: This study demonstrates that anchored ensembles offer an efficient means of quantifying uncertainty within the complex network architecture of deep operator networks that are used as surrogates for physics-based simulations.

Intellectual Merit: A primary contribution of this study is providing an efficient, replicable means for uncertainty quantification within deep operator networks via anchored ensembles. Anchored ensembles encode the prior distribution of network weights (the anchor distribution) by regularizing each network realization to a different sample from that prior. Critically, deep operator networks rely upon two different networks, a branch and a trunk, to form their predictions. Thus, another contribution of this study is integrating the anchored ensembling scheme simultaneously to both networks, producing a reliable confidence interval for a high-dimensional, densely layered network architecture. Regularization takes the form of a penalty term for the network weights that is added to a minimized mean squared error loss function for the data fit. Through this implementation, the anchored ensemble approximates Bayesian inference (Pearce et. al, 2020). Figure 1 presents the results of sample ensemble of 10 networks created to quantify the uncertainty in a nonlinear structural dynamics simulation. The top plot in Figure 1 shows the confidence intervals produced for the residual estimate, while the bottom plot exhibits the overall effect of adding the ensemble predictions to a low-fidelity model and comparing that to the original high-fidelity data.

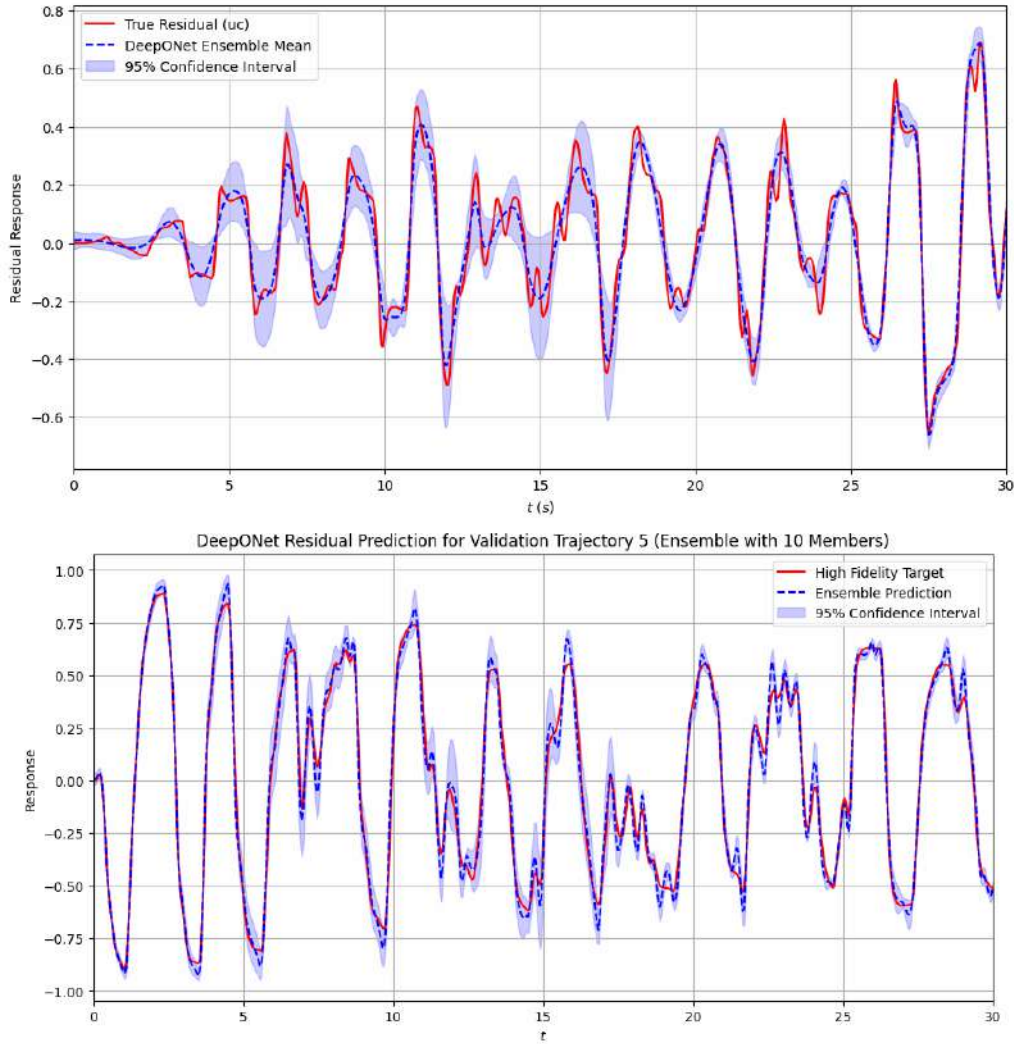


Figure 1: Ensemble confidence intervals for (top) residual estimates and (bottom) original high-fidelity response.

Broader Impacts: As ML methods grow more complex and become embedded in the solution approaches for problems ranging from engineering to sociology, employing measures of confidence is essential for communicable and actionable results because without uncertainty, predictions can lack important context. Within the current example, the addition of confidence intervals provides a more meaningful performance envelope for the structural response, providing a more robust sense of possible outcomes. However, the underlying methodology of using anchored ensembles to quantify uncertainty in complex neural networks is broadly applicable to myriad applications including regression, classification, machine vision, Large Language Models (LLMs) and image generators. All of these techniques rely on neural networks which are conventionally deterministic, which means that finding alternatives and justifying an output are difficult tasks. Since neural networks have hidden internal mechanisms, professional workers cannot see how networks obtain their output, which makes it difficult to trust. This study demonstrates that anchored ensembles can provide an avenue for quantifying uncertainty in the predictions deep operator networks, which helps establish the trustworthiness of their results and can ultimately encourage their wider implementation. Further, this study illustrates that computationally feasible and theoretically justified (i.e., Bayesian inference-based) schemes for uncertainty quantification are possible, even for the most complex network architectures. If professionals and knowledge workers are to trust tools using generative AI or machine learning predictions, they must know what the limits are to an individual prediction and what else lies in the range of possibility given the inputs. Anchored ensembles are a tool which can be used to better understand these limits, qualify the results of an opaque system, and observe that outputs are grounded in truth.

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Code Link: <https://drive.google.com/file/d/1Tzy3JRPJ5eFi2GUKnRp1tmLXE5l6KpJs/view?usp=sharing>

Evaluating the Impact of Rural Broadband Funding on U.S. Agricultural Outputs

Over 41 million Americans lack internet access, with a disproportionate number residing in rural communities (NTIA 2024). The digital divide hinders economic growth, particularly in agriculture, which is becoming increasingly dependent on digital technologies. To address this problem, the FCC launched the Rural Digital Opportunity Fund (RDOF) in 2020, pledging \$20.4 billion to expand broadband to underserved rural areas. This improved connectivity would theoretically enable farmers to adopt AI, analytics, and precision tools that boost income and productivity. Previous studies have linked broadband access to rural economic development (Whitacre et al. 2014), and more recently to agricultural productivity (LoPiccalo 2021). However, there has been little research that evaluates whether broadband funding programs, such as RDOF, actually lead to measurable improvements in farm outcomes.

Previous studies have investigated the broader relationship between broadband access and economic development in rural communities. For example, Whitacre et al. (2014) demonstrates that broadband adoption is associated with increases in rural income and lower unemployment rates in rural areas. More recently, LoPiccalo (2021) finds that broadband penetration enhances crop yields and reduces farm operating costs. However, these studies do not focus on the effects of direct broadband investment programs, such as RDOF. Therefore, a key gap remains: does public funding for broadband causally influence agricultural outcomes?

This study explores the broader question: Do rural broadband subsidies influence agricultural growth in the U.S.? It aims to understand whether broadband infrastructure investments are advancing the economic vitality of rural farming. With U.S. agriculture facing challenges from climate change, global competition, and declining rural populations, internet access has become a driver for resilience and innovation. Yet, policymakers lack clear evidence linking funding to real-world agricultural improvements. This research aims to fill that gap.

By examining the first phase of RDOF funding and its association with farm-related income (earnings generated beyond the direct sale of agricultural products) and the market value of products sold (total revenue generated from the sale of crops and livestock), this paper offers an early look into whether digital infrastructure can serve as an economic catalyst in agriculture. While earlier research provides valuable insight into the positive correlation between broadband and agriculture or rural economic measures, it does not address the role of federal initiatives. Building on the findings of Whitacre et al. (2014) and LoPiccalo (2021), this study uses a difference-in-differences approach to estimate the causal effect of RDOF on farm output. This offers a more targeted evaluation of a major policy initiative and offers clarity to ongoing debates about the role of digital infrastructure in rural economic development.

While the data reveals no statistically significant effect of high RDOF funding—as determined by RDOF funding per rural resident—on the two key agricultural metrics studied, this itself is a crucial finding. Notably, if the estimates were statistically significant, they would suggest that states receiving high RDOF funding may have experienced an additional \$2.65 billion increase in market value of products sold and a \$12.7 million increase in farm related income

relative to states with lower funding. While not definitive, these results signal potentially meaningful economic impacts worth investigating further.

The lack of statistical significance may result from a variety of factors. Likely, it is possible that the economic benefits of broadband access take more time to materialize, as infrastructure must first be built and adopted by users. Alternatively, RDOF funding alone might not be sufficient to drive change in farm-level outcomes. Importantly, states did experience general gains in farm related income and farm product value post-2020, which indicates a broader positive trend in agriculture during this period.

This study highlights the need for long-term policy evaluation and infrastructure planning. While broadband access holds promise, complementary efforts may be required to see the full benefits of connectivity. The results underscore the importance of grounding policy in evidence to shape more effective public investment strategies. As more data becomes available, future research can deepen our understanding of how digital tools reshape farming in America. For now, this work invites policymakers and researchers to prioritize continued evaluation and improvement of broadband programs to ensure the rural communities and farms can benefit from digital innovation.

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Title

The Relationship between Depression and Anxiety Internalizing Symptoms, Pupillometry, and Emotional Memory Encoding

Background

Emotional memory encoding reflects how emotional experience and attention at the time of an event shape later memory (Pilarczyk & Sterna, 2022). Individuals with depressive and anxiety internalizing symptoms demonstrate altered encoding patterns, often showing a bias toward negative stimuli (Dietsche et al., 2014; Klug et al., 2024; Miron & Kalanthroff, 2025). Pupil dilation is a key index and noninvasive measurement of physiological arousal for attentional engagement during encoding (Kafkas, 2024; Xie et al., 2018). Together, these findings suggest that arousal and internalizing symptoms interact to shape emotional memory. Internalizing symptoms refer to inwardly directed forms of psychological distress characterized by disruptions in mood and emotion, including stress, negative affect, and self-focused distress (Konrad et al., 2024; Katsantonis, 2024). In depression and anxiety, these symptoms manifest as persistent low mood and anhedonia (depression) and excessive worry and physiological arousal (anxiety), reflecting overlapping, but distinct patterns of negative emotional processing (Konrad et al., 2024; Spaeth et al., 2024). Depression is associated with altered emotional processing, including negative memory bias and atypical physiological arousal (Dieleman et al., 2010; Xie et al., 2018), alongside cognitive reactivity patterns that reinforce negative encoding (Beck, 2008; Teasdale, 1983). However, physiological findings are mixed: some studies report blunted or inconsistent arousal responses (e.g., reduced pupil dilation), despite stronger memory for negative stimuli (Dieleman et al., 2010; Pilarczyk & Sterna, 2022). Unlike depression, anxiety is characterized by heightened and sustained physiological arousal during emotional encoding (Dieleman et al., 2010; Dolcos & Cabeza, 2002), showing larger and prolonged pupil dilations in response to negative stimuli (Clewett et al., 2018). Importantly, there is substantial individual variation in pupil dilation during emotional encoding, reflecting differences in physiological arousal and attentional engagement across individuals. This variability is particularly relevant in the context of internalizing symptoms. In depression, pupil responses are often blunted or inconsistent, suggesting reduced or dysregulated arousal that may weaken typical arousal–memory coupling. In contrast, anxiety is associated with heightened and sustained pupil dilation, reflecting hyperarousal that may amplify attention toward negative stimuli. Rather than uniformly enhancing memory, these individual differences in pupil dynamics may shape which aspects of an experience are encoded, potentially biasing memory toward emotionally salient details. Examining this variability is therefore critical for understanding how physiological arousal interacts with depression and anxiety to influence emotional memory encoding. In the present article, participants completed the emotion-induced trade-off task, a memory paradigm in which participants encode scenes containing emotionally salient (e.g., negative) objects placed on neutral backgrounds, and are later tested on their memory for each component separately. This task typically reveals a “trade-off” effect, where emotional arousal enhances memory for central objects while impairing memory for peripheral background details. The emotion-induced trade-off task is particularly relevant for studying depression and anxiety because it isolates how emotional arousal biases attention toward salient (often negative) details at the expense of contextual information. This allows researchers to distinguish whether internalizing symptoms are associated with enhanced memory for negative objects or an exaggerated trade-off pattern reflecting maladaptive attentional and encoding processes. This article bridges the gap between physiological arousal, specifically using pupillometry, and emotional memory encoding, finding the differences between people with elevated anxiety and depressive symptoms and healthy individuals.

Central Question

This present article addressed the research question: Do depression and anxiety internationalizing symptoms moderate the relationship between pupil size individual variation, and emotional memory? The research addresses how physiological arousal during emotional memory encoding differs across individuals with depressive symptoms, anxiety symptoms, and healthy controls, and how these differences contribute to negative memory bias. By examining physiological arousal during encoding the project seeks to better understand the pupil dynamics underlying memory encoding patterns affecting anxiety and depression internalizing symptoms, to enhance the understanding of these disorders and provide better treatment via therapy strategies, medications, or interventions.

Intellectual Merit

This project advances understanding of emotional memory by examining how internalizing symptoms shape arousal-related encoding mechanisms. From the emotion-induced trade-off task, we assessed memory for objects, backgrounds, and the trade-off between the two components. We then measured the pupil size difference between viewing negative and neutral scenes to identify a pupil size difference score. We then determined whether depression and anxiety scores moderated the relationship between pupil size difference during encoding and memory performance for objects, backgrounds, and the trade-off. Across models, the most consistent effects emerged for negative object memory, suggesting that internalizing symptoms may selectively disrupt arousal-mediated encoding of emotionally salient objects rather than memory processes more broadly. Moderation analyses ($N = 140$) were conducted to examine whether depression, anxiety, and a composite negative affect measure moderated the relationship between pupil dilation during encoding and specific negative object memory. For depression, the overall model was significant ($R^2 = .101$, $F(4,135) = 2.86$, $p = .026$). The overall model was also significant for anxiety ($R^2 = .102$, $F(4,135) = 2.47$, $p = .048$). Lastly, we tested whether negative affect, an internalizing symptom shared by anxiety and depression, moderated the relationship between pupil size and memory which was significant ($R^2 = .072$, $F(3,135) = 2.92$, $p = .037$). These findings suggest that negative affect internalizing symptoms, shared by depression and anxiety, influence emotional memory encoding of negative object memory. These findings suggest that individuals with negative affect shape how pupillometry influences memory for negative details, indicating that maladaptive encoding biases may emerge. This points to the value of early interventions that target arousal regulation and attentional biases to reduce the preferential encoding of negative details that may contribute to the persistence or worsening of internalizing symptoms. Across models, the most consistent effects emerged for negative object memory, suggesting that internalizing symptoms may selectively disrupt arousal-mediated encoding of emotionally salient objects rather than memory processes more broadly.

Broader Impact

By identifying differences in arousal during memory encoding, the study contributes to dimensional models of psychopathology that can go beyond diagnostic labels and into measurable cognitive and biological mechanisms, understanding more about depression and anxiety. Clinically, understanding how internalizing symptoms alter emotional memory formation may inform more targeted interventions. To illustrate, if maladaptive memory encoding contributes to symptom persistence, therapies that focus on arousal regulation and attentional control could be refined to better address these mechanisms. At a broader level, emotional memory influences how individuals interpret daily experiences, respond to stress, and engage socially. Better understanding the physiological processes underlying negative memory bias can support trauma-informed approaches in education, healthcare, and community settings. Finally, this work encourages interdisciplinary collaboration between cognitive neuroscience and clinical psychology, laying the foundation for future research on treatment response and resilience in mental health, opening up opportunities for reforms in clinical education research, practice, and policy.

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From Pinch to Push: Uncertainty Quantification in Aortic Coarctation Relief Using Polynomial Chaos Expansion: A SimVascular-Based Computational Study

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May 2025

Abstract. Coarctation of the aorta produces abnormal pressure gradients and altered blood flow, while uncertainty in the degree of anatomical relief complicates prediction of post-intervention outcomes. I present a noninvasive uncertainty quantification framework coupling patient-specific fluid–structure interaction simulations in SimVascular with a first-order polynomial chaos expansion (PCE) surrogate. Using vascular geometry and physiological measurements from a 22-year-old patient, I parameterize coarctation relief by a normalized scalar ranging from the baseline coarcted anatomy to a fully dilated configuration. Two deterministic simulations at these endpoints define a linear surrogate for evaluating the sensitivity of spatially averaged pressure and velocity flux across the aortic inlet, outlet, major arterial branches, and vessel wall. The surrogate predicts spatially heterogeneous responses to increasing relief: inlet systolic pressure increases by approximately 5 mmHg, with smaller changes at the outlet and arterial branches, while inlet velocity flux decreases by approximately 20%, with larger relative reductions in major branches. Wall-normal flux remains comparatively insensitive to relief. After the initial high-fidelity simulations, surrogate evaluation requires only inexpensive postprocessing, enabling rapid exploration of intermediate anatomical configurations and propagation of an assumed distribution of relief. These results demonstrate the feasibility of a computationally economical approach to geometry-dependent hemodynamic sensitivity analysis. Further simulations at intermediate relief levels and clinical validation are needed to assess surrogate accuracy and establish its utility for intervention planning.

Background. Coarctation of the aorta (CoA) is a congenital narrowing of the thoracic aorta that leads to elevated proximal arterial pressure, reduced distal perfusion, and long-term cardiovascular complications including hypertension, ventricular hypertrophy, and increased stroke risk. Despite advances in surgical repair and catheter-based interventions such as balloon angioplasty and stenting, postoperative outcomes remain highly variable, with restenosis and residual pressure gradients occurring in a significant subset of patients. This variability arises not only from procedural factors but also from patient-specific anatomical differences, uncertainties in vessel compliance, and heterogeneous remodeling responses following intervention.

Computational hemodynamics has emerged as a powerful tool for analyzing patient-specific CoA physiology, particularly through three-dimensional Navier–Stokes and fluid–structure interaction (FSI) models. However, such high-fidelity simulations are computationally intensive and are typically performed deterministically, yielding a single predicted outcome for a nominal geometry. This paradigm fails to capture uncertainty in stenosis severity, intervention efficacy, or post-procedural vessel geometry—quantities that are inherently variable and clinically uncertain. As a result, clinicians lack rapid, quantitative tools to assess the range of plausible hemodynamic outcomes when planning or evaluating CoA relief.

Clinical measurements used in this study were obtained from a 22-year-old male patient diagnosed with native coarctation of the aorta. Anthropometric assessment yielded a body surface area (BSA) of 2.27 m², with a resting heart rate of 81 bpm. Cardiac output indexed to body surface area resulted in a cardiac index (CI) of 3.3 L/min/m². Noninvasive cuff measurements recorded a blood pressure of 128/70 mmHg, while invasive catheterization revealed ascending aortic (AAo) pressures of 110/57/75 mmHg (systolic/diastolic/mean) and descending aortic (DAo) pressures of 91/52/65 mmHg. All imaging data were acquired using a CT VTI protocol at Lucille Packard Children’s Hospital, enabling high-resolution reconstruction of patient-specific vascular geometry. These data provide realistic physiological boundary conditions and establish a clinically grounded foundation for subsequent uncertainty quantification.

Problem Statement. How can I efficiently quantify and propagate uncertainty in patient-specific aortic geometries through multiscale hemodynamic simulations, in order to predict branch-wise pressure and flow outcomes under varying degrees of stenosis relief?

Intellectual Merit. I present a noninvasive uncertainty quantification framework that couples high-fidelity, patient-specific FSI simulations in SimVascular with a low-order polynomial chaos expansion (PCE) surrogate model. The primary uncertain parameter is the degree of coarctation relief, represented

as a normalized scalar random variable $\xi \in [0, 1]$, where $\xi = 0$ corresponds to the fully coarcted baseline geometry and $\xi = 1$ corresponds to a fully dilated post-intervention geometry. Intermediate values of ξ represent partial relief, modeling uncertainty in procedural outcome, residual stenosis, or early remodeling.

Rather than performing a large ensemble of stochastic simulations, I construct a two-point, first-order PCE surrogate using only two deterministic FSI runs at the extrema $\xi = 0$ and $\xi = 1$. Under the assumption of smooth parametric dependence, this linear PCE captures the leading-order sensitivity of hemodynamic quantities of interest to anatomical uncertainty. Spatially averaged pressures and velocity fluxes are computed over six anatomically and clinically relevant regions: the aortic inlet, aortic outlet, brachiocephalic trunk, left common carotid artery, left subclavian artery, and the vessel wall.

High-fidelity simulations employ a fully coupled FSI formulation with physiologically realistic inflow conditions derived from the patient’s measured cardiac output and heart rate, and outlet boundary conditions consistent with measured pressure distributions. Vessel wall mechanics are modeled using SimVascular’s constrained mixture model framework, allowing deformation-induced changes in lumen geometry to influence flow fields. Figure 1 illustrates representative pressure and wall shear stress fields before and after intervention, highlighting both global pressure relief and localized shear redistribution.

The resulting PCE surrogate reveals a graded, spatially heterogeneous response to coarctation relief. Mean systolic pressure at the aortic inlet increases by approximately 5 mmHg as ξ varies from 0 to 1, reflecting increased forward flow following stenosis removal. This pressure increase attenuates downstream, dropping to 3–4 mmHg at the outlet and to under 2 mmHg in the brachiocephalic trunk, with sub-millimeter variations observed in the carotid and subclavian branches. Velocity flux exhibits a complementary trend, decreasing by roughly 20% at the inlet (from approximately 420 to 330 arbitrary units), with progressively larger relative reductions in downstream branches. Notably, transmural flow remains largely insensitive to ξ , suggesting that bulk uncertainty is dominated by axial transport rather than wall-normal exchange.

This two-point PCE approach reduces the computational cost of uncertainty analysis from approximately 16 hours per stochastic realization to a few minutes of postprocessing, while retaining clinically meaningful accuracy. The framework thus enables rapid sensitivity analysis, supports stochastic optimization of intervention strategies, and provides a principled bridge between high-fidelity biomechanics and uncertainty-aware clinical decision making.

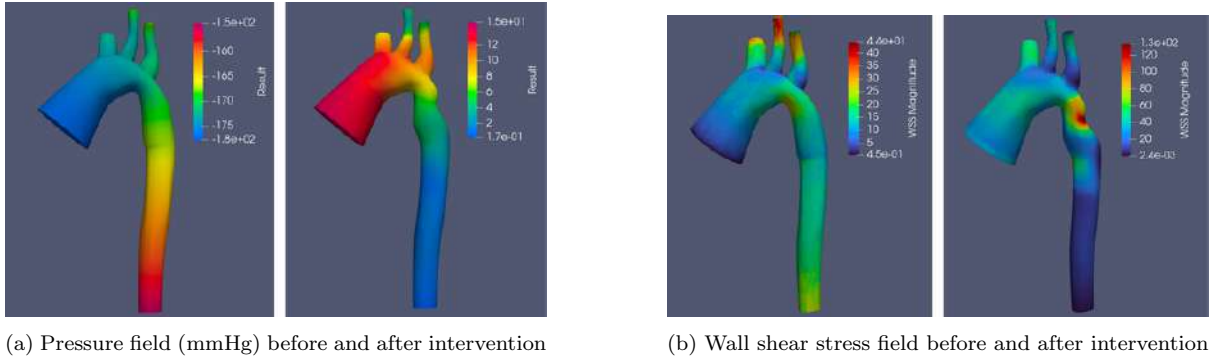


Figure 1: Side-by-side comparison of high-fidelity simulation results for (a) pressure and (b) wall shear stress on patient-specific aortic geometry (model 0237_H_AO_COA).

I introduce a two-point nonintrusive polynomial chaos expansion (PCE) surrogate that models the dependence of spatially averaged pressure and velocity flux on the degree of coarctation relief. The two-point linear PCE surrogate reveals a clear, graded sensitivity of both pressure and velocity flux to coarctation relief: mean systolic pressure at the aortic inlet rises by about 5 mmHg from $\xi = 0$ to 1—diminishing to 3–4 mmHg at the outlet and under 2 mmHg in the brachiocephalic trunk, with sub-millimeter variations in carotid, subclavian, and wall regions—while inlet flux falls by roughly 20% (420→330 abs units), tapering to a 25% drop at the outlet and 30–40% in major branches but remaining essentially unchanged for transmural flow. This efficient surrogate thus captures both the magnitude and spatial distribution of hemodynamic sensitivity to anatomical uncertainty with just two high-fidelity runs.

Broader Impacts. By embedding uncertainty quantification directly into patient-specific cardiovascular simulations, this framework moves computational modeling closer to clinical utility. Clinicians can rapidly explore “what-if” scenarios reflecting incomplete relief, device sizing uncertainty, or early

postoperative remodeling, gaining insight into both expected outcomes and variability across plausible interventions. Such information can inform procedural planning, reduce the likelihood of residual pressure gradients, and guide follow-up strategies aimed at minimizing restenosis risk.

Beyond coarctation of the aorta, the proposed PCE-FSI pipeline is broadly applicable to other vascular pathologies characterized by geometric uncertainty, including aneurysms, peripheral arterial stenoses, and surgically altered vessels. More generally, this work demonstrates how carefully constructed low-order surrogates can unlock the predictive power of high-fidelity biomechanical models without sacrificing computational feasibility, supporting the integration of uncertainty-aware simulation into precision cardiovascular medicine.

Code: All code is accessible at https://github.com/sanchita-chakraborty/PCE_HF_CoarctationModeling.git

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Stability-Guided Subtype Discovery in High-Dimensional Breast Cancer Gene Expression Data

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Abstract: Identifying meaningful patterns in breast cancer gene expression data remains challenging due to its high dimensionality and sensitivity to preprocessing decisions. This paper examines how dimensionality reduction and clustering methods affect potential subtype identification using RNA-Sequencing data from 1,043 breast cancer patients, finding that a two-cluster solution demonstrated the strongest separation and stability. While results suggest reproducible patterns in gene expression, they also highlight the need to distinguish statistically stable clusters from biologically meaningful subtypes before drawing clinical conclusions.

Introduction: Breast cancer is a biologically heterogeneous disease, meaning that tumors classified under the same diagnosis can differ substantially in genetic behavior, prognosis, and response to treatment. The discovery of molecular subtypes through gene expression analysis paved the way for innovative research in therapies based on tumor biology. Researchers can now measure the expression of thousands of genes simultaneously. However, the high dimensionality, skewed distributions, and complex variance structure of gene expression data present significant analytical challenges. Unsupervised learning methods commonly used to identify latent subtypes can produce unstable or misleading results depending on preprocessing choices and modeling assumptions.

This study applies dimension reduction and clustering techniques to RNA-Sequence data from 1,043 breast cancer patients in The Cancer Genome Atlas (TCGA), with the goal of rediscovering biologically meaningful subtypes in a stable and reproducible manner.

Central Question: How can dimension reduction and clustering methods be applied to high-dimensional gene expression data in a way that yields stable, interpretable, and clinically meaningful breast cancer subtypes?

Analytical Approach: To reduce the number of features while retaining genes with substantial variation across patients, 1,000 genes with the highest variance were selected for analysis. Principle Component Analysis (PCA) were used to examine the main sources of gene variation, while Uniform Manifold Approximation and Projection (UMAP) was used to explore whether nonlinear relationships between patients revealed additional structure. Comparing both methods allowed us to examine how different representations of the same data affected clustering results. Applying PCA and UMAP directly to raw gene expression values produced diffuse embeddings with limited separation, consistent with heavy-tailed expression distributions dominating variance structure. After applying the standard $\log(X + 1)$ transformation, embeddings exhibited clearer geometric structure and improved cluster coherence. This illustrates how preprocessing can alter distance relationships that influence unsupervised learning outcomes.

PCA and UMAP both revealed broad structure in the log-transformed data; however, UMAP produced more distinct separation between patient groups, consistent with its preservation of nonlinear neighborhood relationships. This difference was reflected quantitatively in higher silhouette scores for UMAP-based clustering relative to PCA-based clustering. Across clustering methods, $k = 2$ achieved the

highest silhouette scores, particularly under UMAP embeddings (≈ 0.84), indicating stronger separation and compactness relative to $k \geq 3$. The selection of $k=2$ was based on its performance relative to the other cluster numbers tested rather than assuming a fixed number of breast cancer subtypes. While this suggests that two broad groups can be identified in the data, further biological validation would be needed to determine whether they correspond to known molecular subtypes.

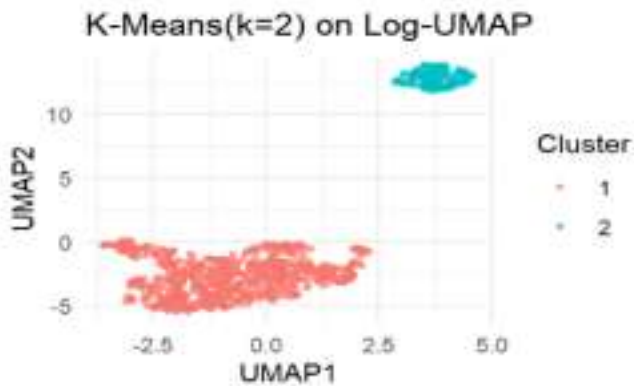


Figure 1. Log transformed UMAP embedding with $k=2$ clusters.

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Stability analysis via repeated subsampling further strengthened this conclusion. Under UMAP + k-means, $k = 2$ achieved near-perfect stability ($\text{ARI} \approx 0.99$), while stability significantly declined for $k \geq 3$. Similar trends were observed across hierarchical clustering. Together, these results provide quantitative evidence that a two-cluster solution remains reproducible across repeated subsampling and that visual separation alone is insufficient to justify subtype claims without stability validation.

One limitation of silhouette scores is that they measure how well clusters are separated, not whether those clusters reflect meaningful biological differences. They can also be affected by the choice of dimensionality reduction method. A high silhouette score should not be taken as sufficient evidence of a biologically meaningful subtype.

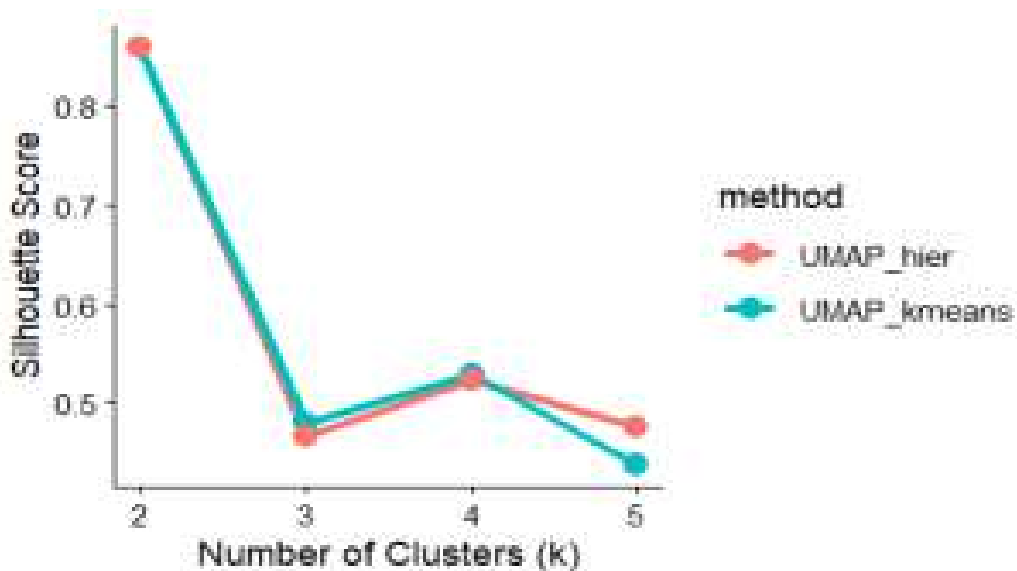


Figure 2. Silhouette score vs number of clusters (k).

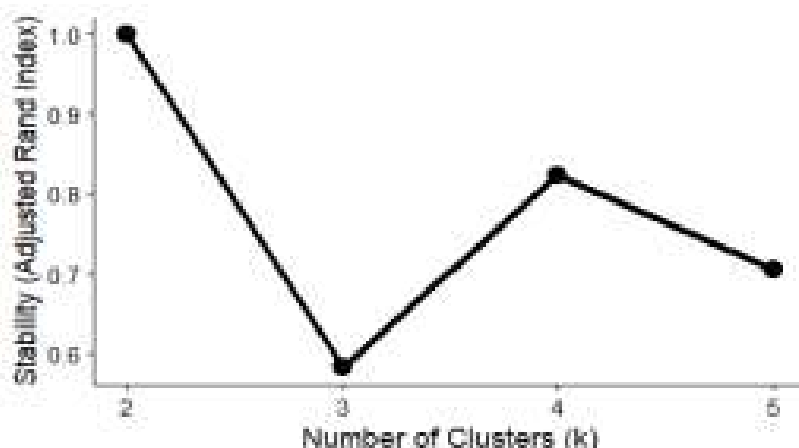


Figure 3. Stability (Adjusted Rand Index) vs number of clusters (k).

Broader Impacts: Reliable subtype discovery has real downstream consequences. If patient groups reflect meaningful molecular differences, they can guide clinical hypotheses about prognosis, responses, and which biomarkers deserve follow-up. At the same time, over-fragmenting patients into unstable clusters risks misleading scientific conclusions and wasting effort on non-reproducible patterns.

More broadly, this work highlights a transferable lesson for societal wellbeing in data science: preprocessing decisions can create or destroy “discoveries.” Pairing interpretability with quantitative stability checks is a practical, accessible template for more responsible unsupervised learning in health contexts. In breast cancer research, these distinctions matter because clusters identified through unsupervised learning can inform studies of prognosis, treatment response, or potential biomarkers. However, these clusters would need to be further validated against established molecular subtypes and clinical outcomes before making conclusions that claim clinical significance.

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Perspective: What is Fair for NCAA Eligibility?

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Abstract

Eligibility policy in the National Collegiate Athletic Association (NCAA) reflects an unresolved tension between educational access and competitive performance. The five-year clock, scholarship limits, and waiver systems are designed to tether athletics to academic progression while preserving competitive balance within capped team structures. Yet, recent reductions in roster sizes may unintentionally constrain opportunities for incoming athletes while creating incentives for programs to exploit flexibility in redshirts, transfers, and international recruitment to maintain competitive advantage. Drawing on observational roster and performance data from men's and women's basketball and cross country between 2015 and 2025, this perspective examines how eligibility extensions, international recruitment patterns, and structural asymmetries reshape opportunity. We argue that fairness in NCAA eligibility must be evaluated not only at the individual level but across cohorts, genders, and time. Ultimately, the debate centers on a foundational question: Is the NCAA structured around the student-athlete, or has it drifted toward the athlete-student?

1. Introduction

Collegiate athletics promotes students' motivation in the classroom while providing an opportunity for students to remain healthy [1]. Yet the rise of competition in the National Collegiate Athletic Association (NCAA) has led to increased stress in collegiate athletes [2]. With student-athletes starting to get paid as of 2021, this has led to increased stress and mental health challenges in recent years [3], [4]. This leads us to ask the question: Is the NCAA structured around the student-athlete, or has it drifted toward the athlete-student? This distinction matters because NCAA rules governing eligibility, roster size, and recruitment influence who has access to collegiate athletic participation and under what conditions.

This perspective examines these questions by considering two sports with different structural characteristics: basketball and cross country. Basketball is a high-visibility sport with tightly constrained roster sizes and significant media attention. Cross country, by contrast, is a non-revenue sport with team-based scoring and broader participation. Yet there has been a roster reduction in recent years. Observations drawn from roster and performance data between 2015 and 2025 provide a

lens for examining how eligibility flexibility and roster constraints interact across sports and genders.

2. Methods

2.1 Data Collection

We draw upon data compiled from publicly accessible sources covering NCAA Division I men's and women's basketball and cross country between 2015 and 2025. For basketball, this includes ESPN [5], SportRadar [6], and BALLDONTLIE [7]. A key limitation is that these sources either do not allow you to scrape data or do not allow you to publicize data. Similarly, cross country results are compiled on TFRRS [8] which restricts scraping and redistribution of datasets.

These source restrictions highlight an important limitation: while patterns can be observed across teams and seasons, the underlying compiled datasets cannot be redistributed publicly. For this reason, the analysis presented here focuses on descriptive trends and observations rather than reproducible statistical modeling. This constraint also prohibits us from publishing important NCAA data. As a result, there is a gap in current NCAA data since its publicity is limited. Companies have limited distribution of this and focus on monetization, rather than putting the athlete at the center by enabling public research.

Specifically, in the NCAA cross country and track and field domain, the largest datasets only have ~500 results [9], and do not cover the majority of athletes, nor focus on both results for men and women. However, club running has public dataset [10], and this relates to NCAA cross country, since club running has increased in size since 2023, in part due to the reduction of the collegiate roster.

3. Findings

International participation appears substantial within NCAA DI Power 4 basketball programs. Among men's teams, more than 14% of athletes appear to originate from outside the United States, while among women's teams the proportion exceeds 20%. International athletes play particularly visible roles on these basketball rosters, and it is beneficial since it provides an opportunity for education. However, NCAA eligibility rules do not establish a universal minimum age for participation, which is especially relevant in cross country since long-distance runners peak in their late twenties [11]. As a re-

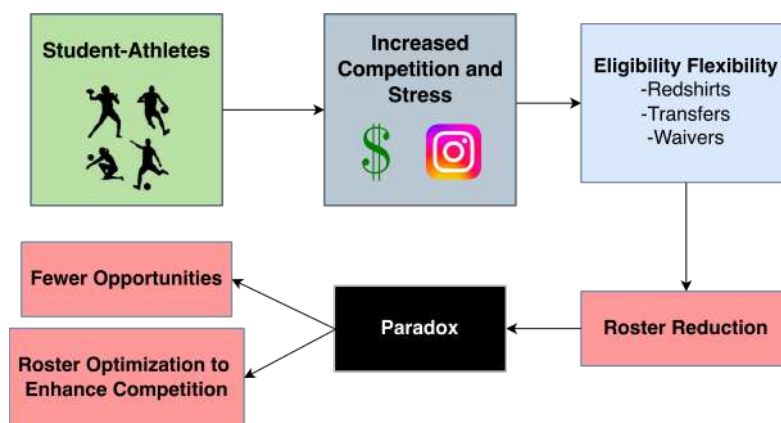


Figure 1: The Student-Athlete Paradox

sult, international athletes may enter NCAA cross country competition after extended development. Publicly reported cases have included freshmen athletes older than 25 years of age competing in distance events. On one hand, this pathway provides access to higher education and scholarship opportunities. On the other hand, it may affect competitive balance in sports where physiological performance peaks later in adulthood.

Roster size reductions across non-revenue sports appear to have changed participation dynamics. In cross country and track and field programs, the varsity roster totals at one university declined from 114 athletes in 2023–24 and 116 athletes in 2024–25 to 81 athletes in 2025–26. Over the same period, the number of freshmen on the varsity roster fell from 32 to 4. Concurrently, a newly formed club team at the same institution listed 74 members, including 54 freshmen and 16 sophomores, in its first season, and brought one of their NCAA coaches to the club level, breaking multiple national club records. While this is beneficial for individual athletes, it could create opportunities for universities to skirt the rules by artificially increasing their roster size by leading a club. At the same time, it has the ability to destroy club competition by filling clubs with NCAA-caliber athletes.

4. Discussion

Taken together, these observations illustrate how NCAA policy choices interact in complex ways. Eligibility flexibility, through redshirts, transfers, and waivers, can extend athlete participation timelines. At the same time, roster reductions limit the number of available positions within varsity programs.

When these forces operate simultaneously, a paradox emerges. Policies intended to maintain competitive balance and academic alignment may reduce opportunities for freshmen and walk-ons while encouraging programs to optimize roster composition through recruitment strategies, including international pipelines and eligibility management.

This tension is particularly visible in sports with different economic profiles. Revenue-generating sports such as football and men’s basketball often drive institutional finances and media attention. Non-revenue sports such as cross country, however, are more directly affected by institutional budgeting decisions and roster management policies.

From a fairness perspective, the question is not simply whether individual athletes deserve extended eligibility or recruitment opportunities. Rather, the broader issue is how eligibility rules distribute opportunity across cohorts of athletes over time. Additionally, these athletes should be given the opportunity to enjoy the sport. However, many have to sacrifice academics and prioritize athletes at the expense of their mental health [12].

5. Conclusion

NCAA eligibility policy sits at the intersection of education, competition, and institutional economics. While eligibility flexibility and international recruitment can expand educational access for individual athletes, reductions in roster sizes and finite participation opportunities create new structural constraints.

Understanding fairness in this context requires moving beyond individual cases toward a systemic perspective. Policies governing eligibility and roster management shape who is able to participate in collegiate athletics, how long they remain eligible, and how opportunities are distributed across generations of athletes.

Ultimately, collegiate athletics should remain aligned with the educational mission of universities. Eligibility structures should therefore prioritize broad participation, student mental health, and academic development rather than purely competitive outcomes. Ensuring that policies support both athletic participation and academic well-being is essential for preserving the integrity of the student-athlete model.

Ethics

For anonymity, we do not list the names of specific universities nor players personal identifiable information. Additionally, due to data collection terms of service, detailed results are not displayed.

Acknowledgments

We would like to thank the National Running Club Database and the CRC Coaches Poll for their support in this project.

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Toward Durable Peacemaking: Evaluating Intrastate Peace Agreement Provisions via Penalized Survival Analysis

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Abstract

In the post-Cold-War era, peace agreements are the most common way of terminating intrastate conflicts, which are responsible for tens of thousands of deaths globally each year. Prior work has linked specific provisions, such as peacekeeping, and the mix of terms in an agreement to how long peace lasts. A penalized survival model that weighs those provisions at the same time, and retains only the associations the data support, is still missing. In 336 intrastate agreements, reaffirmation of a prior agreement is associated with lower collapse risk ($HR = 0.63$, 95% CI 0.37–0.91), as is a longer stretch of years since last conflict ($HR = 0.93$ per year, 95% CI 0.76–0.99). The Middle East point estimate is higher than Africa’s, but that interval includes 1, and ceasefire provisions are not associated with greater durability.

Code and Dataset: <https://github.com/bherbst5/peace-agreement-survival>

1. Introduction

Modern civil wars are increasingly frequent, deadly, and prone to relapse [1]. The Sudanese Civil War alone is estimated to have caused tens of thousands of deaths since it began in April 2023 [2]. Further, post-Cold War conflicts conclude more often with negotiated settlements than military victories [3]. However, these agreements remain fragile, with nearly 40% failing within five years [4]. Establishing lasting peace requires resolving foundational incompatibilities through substantive agreements that often contain several distinct provisions [4], [5].

Existing scholarship has illuminated specific peace terms, such as power-sharing or third-party guarantees, and has compared bundles of provisions [5], [6], [7]. The remaining gap is a penalized model that weighs many provisions at once and keeps only the associations the data support.

To address this methodological gap, our analysis utilizes survival analysis and LASSO penalization [8] to weigh the simultaneous influence of multiple provisions. This approach offers interpretable feature importance measures for the provisions that are associated with longer-lasting intrastate peace.

Peace negotiations are frequently complicated by multiple “veto players” whose consensus is required for any policy change [9]. By identifying the few most impactful provisions, this research equips negotiators with a short list of terms to target in cases where multiple parties must agree and consensus is difficult to obtain.

2. Methods

2.1 Data

Our initial dataset is the UCDP’s Peace Agreement Dataset (PAD) version 22.1, which contains 374 peace agreements [4]. Excluding 32 interstate conflicts and 6 intrastate agreements with no usable duration leaves 336 intrastate agreements signed between 1975 and 2021. 116 of these agreements experienced collapse (the event of interest) and 220 remained in force through the censoring date of December 31, 2021. The outcome variable is agreement duration (measured in days from the date of signing to the date of collapse or censoring).

2.2 Analysis

Peace agreement survival was first examined non-parametrically using Kaplan–Meier estimators (see Figure 1), stratified by conflict region.

Survival was subsequently modeled using two complementary Cox proportional hazards approaches. Both models share a 52-column design matrix comprising 28 binary provision indicators, one ordinal variable (years since last conflict activity, in inactive years between the end of fighting and signature), ten dummy columns for four categorical variables (region, incompatibility type, agreement type, and frame), and 13 interaction terms. All predictors were standardized (mean 0, SD 1) prior to estimation. Hazard ratios below are on the original scale. Figure 2 compares absolute coefficients on the standardized scale, so that a rare indicator is not ranked above a continuous predictor merely because its raw coefficient is large. Standard errors for the unpenalized model are clustered by conflict.

The baseline model was estimated by maximum partial likelihood. A Grambsch–Therneau test on $\log(t)$ flagged six of the 52 predictors at $p < 0.05$, including elections and national dialogue. About three rejections are expected by chance. An extended unpenalized model re-entered violators with $\log(t)$ terms; its national dialogue term is negative ($p = 0.08$), im-

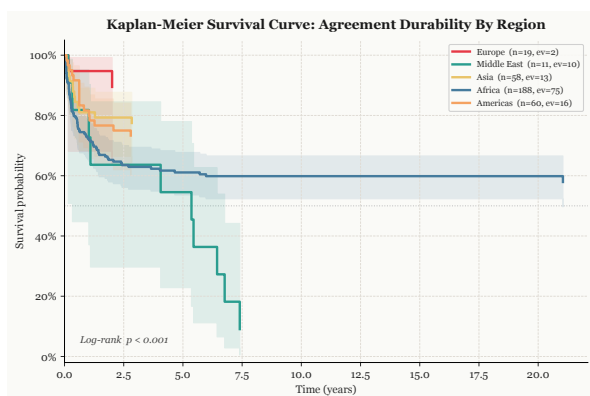


Figure 1: Kaplan-Meier Survival Curves By Region (with shaded 95% confidence intervals)

plying a higher early hazard that is about 1 by year five. The penalized model used LASSO regularization in scikit-survival 0.23.1 and omits time-varying terms, since time-averaged hazard ratios suffice for selecting predictors and extra terms would complicate shrinkage and risk overfitting; its hazard ratios are therefore averages over follow-up. Reported estimates use $\lambda = 0.040$. Intervals are percentiles from 200 conflict-level resamples at that penalty. An endpoint of 1.00 means the penalty dropped the term in at least 2.5% of draws; the count of draws that keep the term is given beside each estimate.

3. Results

The LASSO model retains 18 of 52 predictors at $\lambda = 0.040$. On the standardized scale in Figure 2, reaffirmation is the largest association and corresponds to a lower collapse hazard ($\beta = -0.46$, HR = 0.63, 95% CI : 0.37–0.91; kept in 198 of 200 draws), followed by years since last conflict (HR = 0.93 per year, 95% CI : 0.76–0.99; kept in 196 of 200). The Middle East coefficient is next ($\beta = +0.99$, HR = 2.69; kept in 121 of 200, so the interval is 1.00–5.34), from 11 agreements and 10 collapses. Europe’s point estimate is lower than the African reference ($\beta = -0.59$, HR = 0.55; kept in 169 of 200, interval 0.20–1.00). National dialogue (HR = 1.66, kept in 182), ceasefire provisions (HR = 1.36, kept in 162), the amnesty $\times$ reconciliation interaction (HR = 0.91, kept in 160), and referendum provisions (HR = 0.77, kept in 107) also have an endpoint at 1. Eight predictors remain at the 1-SE penalty ($\lambda = 0.064$): the Middle East, Europe, reaffirmation, years since last conflict, national dialogue, ceasefire, amnesty $\times$ reconciliation, and integration into government $\times$ national dialogue.

4. Discussion

Reaffirmation has the largest standardized association. Its conflict-level interval excludes 1, and it remains in the model at the 1-SE penalty. Revisiting past com-

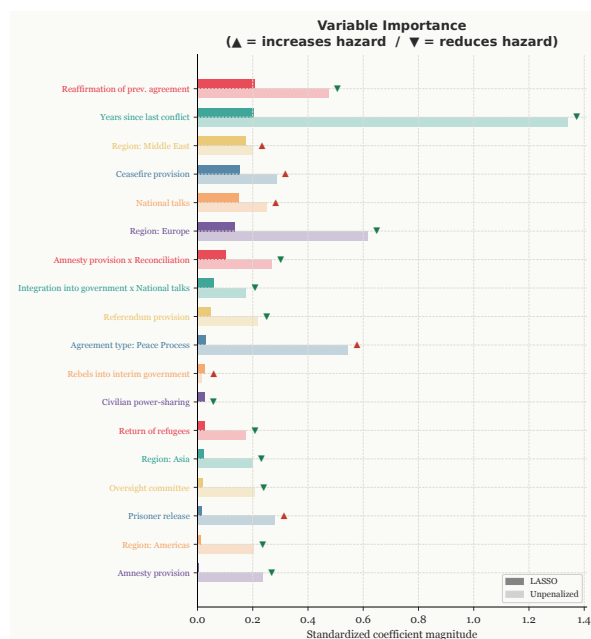


Figure 2: Ranked Peace Agreement Variable Importance

mitments might enable negotiators to consolidate the strengths of earlier agreements. Years since last conflict meets the same interval criteria, though narrowly: its upper bound is 0.99. The Middle East point estimate is also large, but its interval includes 1 and it rests on only 11 agreements. Europe’s point estimate is lower than Africa’s, but its interval includes 1 as well. Referendum provisions and the pairing of amnesty with reconciliation point toward lower hazard, but both intervals include 1 and the referendum term does not survive the 1-SE rule, so these patterns are only suggestive. Ceasefire provisions remain at the 1-SE penalty and point toward higher collapse risk, but that interval also includes 1. Because ceasefires are plausibly signed in conflicts that have not yet settled, this association may reflect those conflicts rather than the clause itself.

The estimates offer a short list of terms for negotiators who cannot prioritize every attractive clause: build on an earlier agreement, and treat a longer period before signature as favorable context. Referendums, paired amnesty and reconciliation, and ceasefire language are too uncertain to be treated as hard requirements.

5. Conclusion

Survival analysis of 336 intrastate peace agreements identifies reaffirmation of previous agreements and years since last conflict as the two factors most reliably associated with longer-lasting peace. The associations for regional context, ceasefire provisions, referendums, and paired amnesty and reconciliation are present but less certain. These results suggest that peace agreement durability is shaped by both the context that negotiators inherit and the terms that they stipulate.

Generative AI Usage

We used AI for coding and paper editing. All content ideation is our own, and we take full responsibility for our work.

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Deploying Anchored Ensembles for Deep Operator Network Surrogate Models

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Abstract: Deep neural networks are deterministic without fundamentally altering their architecture; however, they are employed in a range of disciplines that increasingly ask for decision-making, judgment, and other complex tasks with no definite answer. This means that when a neural network is given identical inputs, it will yield identical outputs without variation. Because complex tasks require answers to be justified, models must be able to indicate what degree of certainty can be assigned to their answer, and most statistical methods require variation to estimate uncertainty. Bayesian neural networks effectively utilize statistical priors to estimate uncertainty, but they are computationally expensive. Monte Carlo dropout randomly removes parameters from the network to synthesize variability; however, this introduces noise which is not informed by explicit priors. This article examines anchored ensembles, which introduce variability informed by priors without incurring the prohibitive expense of Bayesian neural networks. We apply them to deep operator networks trained on the difference between low-fidelity physics simulations and high-fidelity simulations, so that predictions of safety and structural tolerance can be qualified.

Background: Developing full-scale models of physical systems can yield predictions with high fidelity, but these often come at great computational expense. Further, relying on machine learning (ML) models to fully replace these models as surrogates completely abandon any known physics. In lieu of full replacement, ML models such as deep operator networks can also be used to capture the discrepancy, or residual, between a computationally efficient low-fidelity representation and the original high-fidelity model (De and Brewick, 2024). However, these predictions are inherently deterministic, which leads to another issue: ML methods can be overconfident in their predictions and output.

Within rigorous engineering applications this overconfidence can manifest as an absence of uncertainty, which diminishes the utility of both an AI model and its predictions. Uncertainty can be accounted for through techniques such as Monte Carlo dropout or through approximate Bayesian methods (Ghorbanian et. al, 2025); however, because of their high parameter count, quantifying uncertainty through probability distributions of network weights, as in Bayesian neural networks, is far too computationally expensive (Pearce et. al, 2020). Furthermore, neural networks risk experiencing uncertainty collapse when more than one is trained on a dataset (Kirsch, 2024). Thus, simply training an ensemble of models and computing population statistics for confidence intervals typically yields an overconfident, narrow prediction interval because the network realizations lack sufficient diversity. To improve uncertainty quantification within ML techniques, this study explores using anchored ensemble methods to quantify the uncertainty within deep operator networks that are subsequently used to conduct physics-based simulations. Specifically, the anchored ensembles yield confidence intervals and prediction envelopes that can replace standard deterministic predictions.

Central Focus: This study demonstrates that anchored ensembles offer an efficient means of quantifying uncertainty within the complex network architecture of deep operator networks that are used as surrogates for physics-based simulations.

Intellectual Merit: A primary contribution of this study is providing an efficient, replicable means for uncertainty quantification within deep operator networks via anchored ensembles. Anchored ensembles

encode the prior distribution of network weights (the anchor distribution) by regularizing each network realization to a different sample from that prior. Critically, deep operator networks rely upon two different networks, a branch and a trunk, to form their predictions. Thus, another contribution of this study is integrating the anchored ensembling scheme simultaneously to both networks, producing a reliable confidence interval for a high-dimensional, densely layered network architecture. Regularization takes the form of a penalty term for the network weights that is added to a minimized mean squared error loss function for the data fit. Through this implementation, the anchored ensemble approximates Bayesian inference (Pearce et. al, 2020). Figure 1 presents the results of sample ensemble of 10 networks created to quantify the uncertainty in a nonlinear structural dynamics simulation. The top plot in Figure 1 shows the confidence intervals produced for the residual estimate, while the bottom plot exhibits the overall effect of adding the ensemble predictions to a low-fidelity model and comparing that to the original high-fidelity data.

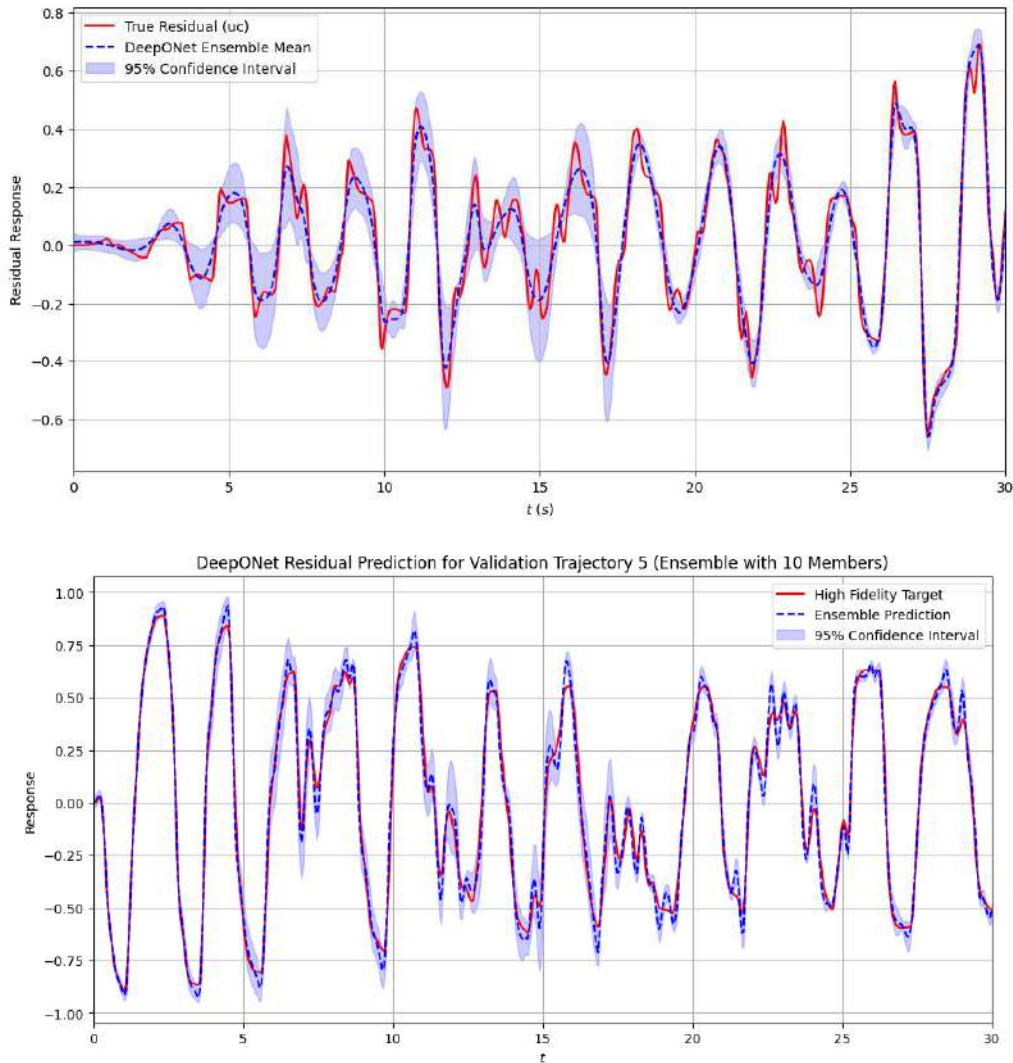


Figure 1: Ensemble confidence intervals for (top) residual estimates and (bottom) original high-fidelity response.

Broader Impacts: As ML methods grow more complex and become embedded in the solution approaches for problems ranging from engineering to sociology, employing measures of confidence is essential for

communicable and actionable results because without uncertainty, predictions can lack important context. Within the current example, the addition of confidence intervals provides a more meaningful performance envelope for the structural response, providing a more robust sense of possible outcomes. However, the underlying methodology of using anchored ensembles to quantify uncertainty in complex neural networks is broadly applicable to myriad applications including regression, classification, machine vision, Large Language Models (LLMs) and image generators. All of these techniques rely on neural networks which are conventionally deterministic, which means that finding alternatives and justifying an output are difficult tasks. Since neural networks have hidden internal mechanisms, professional workers cannot see how networks obtain their output, which makes it difficult to trust. This study demonstrates that anchored ensembles can provide an avenue for quantifying uncertainty in the predictions deep operator networks, which helps establish the trustworthiness of their results and can ultimately encourage their wider implementation. Further, this study illustrates that computationally feasible and theoretically justified (i.e., Bayesian inference-based) schemes for uncertainty quantification are possible, even for the most complex network architectures. If professionals and knowledge workers are to trust tools using generative AI or machine learning predictions, they must know what the limits are to an individual prediction and what else lies in the range of possibility given the inputs. Anchored ensembles are a tool which can be used to better understand these limits, qualify the results of an opaque system, and observe that outputs are grounded in truth.

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Code Link: <https://drive.google.com/file/d/1Tzy3JRPJ5eFi2GUKnRp1tmLXE5l6KpJs/view?usp=sharing>

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