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Computational fluid dynamics modelling of hemodynamics in aortic aneurysm and dissection: a review

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Hemodynamic analysis based on computational fluid dynamics (CFD) modelling is expected to improve risk stratification for patients with aortic aneurysms and dissections. However, the parameter settings in CFD simulations involve considerable variability and uncertainty. Additionally, the exact relationship between hemodynamic features and disease progression remains unclear. These challenges limit the clinical application of aortic hemodynamic models. This review presents a detailed overview of the workflow for CFD-based aortic hemodynamic analysis, with a focus on recent advancements in the field. We also conducted a systematic review of 27 studies with large sample sizes ($n > 5$) that examine the hemodynamic characteristics of aortic aneurysms and dissections. Some studies identified consistent relationships between hemodynamic features and disease progression, reinforcing the potential for clinical application of aortic hemodynamic models. However, limitations such as small sample sizes and oversimplified patient-specific models remain. These findings emphasize the need for larger, more detailed studies to refine CFD modelling strategies, strengthen the connection between hemodynamics and diseases, and ultimately facilitate the clinical use of aortic hemodynamic models in disease management.

KEYWORDS

hemodynamics, CFD, aortic aneurysm, aortic dissection, wall shear stress

1 Introduction

Aortic diseases, particularly aneurysms and dissections, remain significant global health threats. Between 1990 and 2019, fatalities from aortic aneurysms increased by 82.1% (Wang Z. et al., 2022). The true incidence of aortic dissection may be underestimated, as many patients die before receiving a diagnosis. Evidence also suggests that the number of aortic dissection cases has risen over time (LeMaire and Russell, 2011).

Currently, imaging is the primary method for diagnosing aortic aneurysms and dissections, providing anatomical parameters that guide therapeutic protocols. However, relying solely on anatomical risk assessments may overlook high-risk patients. For instance, while abdominal aortic aneurysms with a diameter over 5–5.5 cm or a growth rate above 1 cm per year typically prompt surgical intervention, some smaller aneurysms can also be prone to rupture (Spanos et al., 2020; Abdelkhalek et al., 2022; Ashkezari et al., 2022). Similarly, certain type B aortic dissections (TBAD) that appear clinically stable may in fact

be unstable, contributing to a persistent in-hospital mortality rate in recent years (Evangelista et al., 2018).

Recent studies increasingly suggest that hemodynamic factors could improve risk stratification for patients with aortic aneurysms or dissections (Zilber et al., 2021; Ramaekers et al., 2023). Aortic hemodynamics can be assessed through clinical measurements or *in silico* analysis based on computational fluid dynamics (CFD). Compared to clinical measurements, CFD modelling offers more precise spatiotemporal predictions at a lower cost. However, many clinicians face challenges in implementing CFD modelling and interpreting its results due to insufficient training in this area.

This review aims to present the recent advancements in CFD modelling for predicting aortic hemodynamics, providing guidance on conducting CFD simulations and analyzing hemodynamic indicators. We also reviewed several large sample studies to summarize findings on the relationships between hemodynamic metrics and aortic diseases, while highlighting limitations that currently hinder the clinical application of aortic hemodynamic models. Finally, we offer recommendations for future research on CFD-based hemodynamic analysis in aortic aneurysms and dissections.

2 Features of aortic hemodynamics

The aorta, the largest blood vessel in the body, serves as the primary conduit for delivering oxygenated blood throughout the body (Hall and Guyton, 2011). Hemodynamics within the aorta is highly complex, largely due to its unique anatomy. The aorta's centerline is non-planar and curved in three dimensions (Chandran, 1993). As blood is ejected from the left ventricle, it undergoes impingement, swirling, separation, and reattachment as it navigates the tortuous path of the aorta. Additionally, the large size of the aorta leads to the development of secondary flows within the lumen cross-section (Tse et al., 2013).

The numerous branches of the aorta contribute to the redistribution of blood flow, adding to the complexity and uncertainty of the aortic hemodynamics. The aorta extends from the left ventricle to the lower abdomen, tapering in lumen size and branching multiple times along the way. It typically has three main branches in the aortic arch that supply blood to the upper body, as well as several branches in the descending aorta that deliver blood to internal organs. However, the branching patterns of the aorta exhibit considerable variability among individuals (Mustafa et al., 2017). Blood flow is redistributed at these bifurcations, and the presence of lesions, such as stenosis, further complicates the flow dynamics (Dabagh et al., 2015).

Significant changes in the shape and spatial position of the aortic vessel wall further contribute to the complexity of intraluminal hemodynamics. The aorta's compliance is high, accounting for more than half of the total compliance of the arterial system in healthy young adults (Pagoulatou et al., 2021). The aorta stretches to accommodate the large volume of blood ejected during systole and recoils to maintain downstream blood flow during diastole (Tanweer et al., 2014). Additionally, the aortic root experiences periodical towed and relaxed movements due to ventricular traction, which are transmitted to the ascending aorta (Wei et al., 2019). Given these factors, predicting aortic hemodynamics through CFD modelling presents significant challenges.

3 Workflow in CFD modelling for aortic hemodynamics

Partial differential equations are commonly used to describe fluid flow and related phenomena. However, in many cases, these equations cannot be analytically solved. CFD modelling addresses this challenge by using discretization methods to approximate partial differential equations as a system of algebraic equations (Feiger et al., 2020). These algebraic equations are then solved through computational techniques. The obtained numerical solution provides results at discrete locations in both space and time.

Despite its potential, CFD modeling for aortic hemodynamics faces several challenges, including high computational demands, long processing times, and the complexity of the process, which requires multidisciplinary collaboration (Cebal and Meng, 2012; Feiger et al., 2020; Kamada et al., 2022). Additionally, the highly patient-specific nature of these simulations adds further complexity. However, the successful use of CFD modelling in cardiovascular diseases, such as noninvasive fractional flow reserve, has strengthened confidence in its broader clinical potential (Hu et al., 2024). Researchers remain committed to advancing CFD techniques for aortic diseases management, aiming to bridge the gap between research and clinical practice.

CFD modelling of hemodynamics involves seven stages: clinical imaging, geometry reconstruction, discretization, boundary condition specification, solution setup, post-processing, and validation (Morris et al., 2016).

3.1 Clinical imaging

Traditional clinical imaging methods for geometry reconstruction in hemodynamic studies include digital subtraction angiography (DSA), contrast-enhanced computed tomography (CECT), computed tomography angiography (CTA), magnetic resonance imaging (MRI), and magnetic resonance angiography (MRA) (Rayz and Cohen-Gadol, 2020). DSA is an invasive technique that provides two-dimensional projections of the vasculature. It can be expanded to three dimensions through 3D rotational angiography (3DRA), which acquires and combines multiple projections by rotating the C-arm. 3DRA is considered the gold standard for generating intracranial aneurysm (IA) models (Steinman and Pereira, 2019). CECT and CTA are the most commonly used imaging method, offering high spatial resolution and rapid acquisition times (Ren et al., 2016). However, all of these methods, including DSA, 3DRA, CECT, and CTA, involve ionizing radiation and nephrotoxic contrast agents. MRI is a technique free from ionizing radiation but requires longer acquisition times and offers lower spatial resolution (Wan Ab Naim et al., 2014). Unenhanced MRA techniques are noninvasive. Time-of-flight MRA is a representative unenhanced technique that uses repeated pulses to differentiate between stationary tissues and flowing blood. However, this technology performs poorly in regions with slow flow (François et al., 2008). This limitation can be addressed with contrast-enhanced MRA. In addition to lumen modelling, MRI can also provide valuable data on wall content through black blood MRI scans (Arzani et al., 2014). Wang et al. (2022) systematically reviewed the applications of MRI in the hemodynamic study of TBAD.

Moreover, ECG-gated imaging techniques have been employed to capture dynamic variations in the aortic wall position throughout the cardiac cycle. Capellini et al. (2021) reconstructed ascending aortic geometries from ECG-gated CTA data and examined how geometric variations influence aortic hemodynamics. Similarly, Midulla et al. (2012) used ECG-gated cine MRA to capture aortic wall movements and performed dynamic mesh simulations to predict hemodynamics in patients treated by thoracic endovascular aortic repair.

3.2 Geometry reconstruction

Based on the acquired image dataset, geometry reconstruction can proceed, involving several steps such as image segmentation, smoothing, simplification, and treatment of the inlet and outlet.

Segmentation methods have evolved from 2D plane segmentation and lofting to 3D volumetric segmentation based on intensity thresholding, and now to fully automated segmentation powered by deep learning (Steinman, 2002; Antiga et al., 2008; Cao et al., 2019; Chen et al., 2021). A state-of-the-art deep learning-based framework is able to identify the true and false lumen, as well as local characteristics of the primary tear, in patients with TBAD (Chen et al., 2021).

Typically, some degree of smoothing is applied to the segmented model to facilitate successful spatial discretization. However, this smoothing must be performed carefully to avoid altering the geometry and volume size. Paritala et al. (2023) investigated intra-team variability in hemodynamic predictions for IAs and found that smoothing contributed the most to variations in wall parameters. Nonetheless, its impact on aortic hemodynamics remains underexplored.

Early hemodynamic studies often employed some simplifications, such as neglecting variations in vessel diameter, using circular cross-sections, and omitting downstream branches (Caballero and Laín, 2013). These simplifications can significantly affect the accuracy of the hemodynamic predictions. As computational power improves, the use of complete, patient-specific aortic models is increasingly recommended (Wan Ab Naim et al., 2014). Stokes et al. (2023b) investigated the impact of neglecting minor aortic branches on TBAD hemodynamics and found that this simplification could lead to differences of 60%–75% in clinically relevant metrics.

Truncating and extending the inlet and outlet appropriately ensures that the blood flow in the region of interest is not affected by boundaries. These strategies are typically determined based on the research needs. While some studies have quantitatively assessed their impact on intracranial hemodynamics (Pereira et al., 2013; Hua et al., 2015), similar analyses on the aorta are relatively rare. Chi et al. (2022) highlighted the importance of appropriate inlet truncation by comparing the effects of truncating at the middle of the ascending aorta versus at the aortic valve.

Geometry reconstruction can be carried out using various software tools, including Mimics (Geiger et al., 2016), SimVascular (Updegrave et al., 2017), CRIMSON (Arthurs et al., 2021), VMTK (Williams et al., 2022), Simpleware ScanIP (Stokes et al., 2023a), 3D Slicer (Pieper et al., 2004), ITK-SNAP (Yushkevich et al., 2016), OsiriX (Rosset et al., 2004), GIMIAS (Larrabide et al.,

2009), MITK (Wolf et al., 2004), DetecModeling (Ding et al., 2024). Some tools, such as SimVascular and DetecModeling, incorporate advanced machine learning algorithms, which streamline the reconstruction process and reduce the time and effort required.

To ensure that the reconstructed geometric model is suitable for CFD simulation, several measures should be taken (Sveinsson Cepero and Shadden, 2025). First, the research team should consist of experienced biomedical engineers familiar with human anatomy. A comprehensive geometric reconstruction protocol should be developed, covering key aspects such as intensity thresholding, smoothing extent, and inlet and outlet truncation and extension. All operators must undergo consistent training, and each reconstruction task should be performed by at least two operators. Any disagreements between operators should be resolved by experienced team members (Paritala et al., 2023). From a technical standpoint, advanced automated algorithms should be prioritized to reduce operator-induced uncertainties (Maher et al., 2020). Additionally, sequentially combining advanced algorithms—such as imaging quality enhancement, centerline extraction, and segmentation—can further improve the accuracy of the reconstruction process (Lesage et al., 2009; Maher et al., 2021).

3.3 Spatial discretization

Once the geometric reconstruction based on clinical images is completed, the process can proceed similarly to CFD simulations in other fields, starting with spatial discretization, or grid generation. The computational domain is typically discretized into tetrahedral, hexahedral, or polyhedral meshes using advanced software or algorithm. A finer boundary layer mesh should be generated in regions adjacent to the arterial wall to accurately predict near-wall flow and wall parameters. Mesh resolution significantly impacts the accuracy of hemodynamic predictions (Aycan et al., 2023). Although this has primarily been demonstrated in studies of IAs and coronary arteries (Prakash and Ethier, 2001; Hodis et al., 2012), it can be logically extended to the aorta. Moreover, the mesh resolution required for mesh independence varies for different hemodynamic parameters, such as velocity and wall parameters (Prakash and Ethier, 2001; Valen-Sendstad and Steinman, 2014; Evju et al., 2017), and should be carefully determined.

3.4 Boundary conditions

To obtain accurate hemodynamic predictions, it is essential to establish appropriate boundary conditions for the computational domain. Clinically measured, patient-specific data, such as blood flow velocity, pressure, and arterial wall movements, are considered ideal for hemodynamic simulations (Rayz et al., 2008; Perera et al., 2020); however, these data are often unavailable in clinical practice.

For the inlet boundary condition, the empirical flow waveform from literature is typically used in aortic hemodynamic simulations. However, studies have shown that deviations in the inlet flow rate, flow waveform shape, and inlet velocity profile can hinder the accurate prediction of patient-specific hemodynamics (Morbiducci et al., 2013; Youssefi et al., 2018; Armour et al., 2021; Stokes et al., 2023a). Armour et al. (2021) found that a

reduction in stroke volume resulted in a decrease in both velocity and wall shear stress, whereas the flow waveform shape significantly affected the predicted pressure. Furthermore, their results also revealed that three inlet velocity profiles—three-dimensional, through-plane, and flat profiles—yielded similar predictions for velocity and wall shear stress; however, the through-plane profile predicted a more accurate pressure distribution. Similarly, Stokes et al. (2023a) found that the choice of the inlet velocity profile significantly influenced oscillatory shear and helicity in the aorta. Although 4D-flow MRI can measure the temporal three-dimensional velocity profile, it has been shown to underestimate the peak flow rate and velocity (Cherry et al., 2022). Therefore, 2D-flow MRI, which acquires axial velocity data (i.e., through-plane profile), is recommended for measuring patient-specific inlet boundary conditions (Armour et al., 2021; Stokes et al., 2023a).

For the outlet boundary condition, obtaining clinically measured data is more challenging due to the presence of multiple outlets and the small size of the downstream branches. In aortic hemodynamic simulations, simplified outlet boundary conditions, such as constant or pulsatile pressure (O'Rourke et al., 2012; Filipovic et al., 2013; Zambrano et al., 2016), or specific flow division (Peng et al., 2019; Zhang et al., 2023), are commonly used. However, the neglect of the downstream arterial system in simulations using these simplified boundary conditions often results in non-physiological predictions, particularly regarding blood pressure. Furthermore, prescribing equal pressure for all outlets causes the downstream flow distribution to deviate from reality (Chnafa et al., 2018). Coupling low-dimensional models, such as the lumped parameter model (0D) or distributed parameter model (1D), at outlets to perform multi-scale simulations is an effective option for predicting hemodynamics closer to physiological conditions (Soudah et al., 2014; Stokes et al., 2021). A comprehensive introduction to these low-dimensional models for hemodynamic predictions can be found elsewhere (Shi et al., 2011; Zhou et al., 2019; Chi et al., 2022; Garber et al., 2022).

For the aortic vessel wall, variations in the shape and spatial position due to compliance and cardiac traction are often ignored in simulations, which typically assume that the wall is rigid with no-slip boundary conditions (Xu et al., 2021; Li et al., 2023; Mutlu et al., 2023). However, the assumption of a rigid wall has been shown to cause significant deviations in the blood flow velocity and wall parameters in hemodynamic predictions (Ene et al., 2014; Bonfanti et al., 2017; Qiao et al., 2019; Athani et al., 2022). Ene et al. (2014) compared fluid-structure interaction (FSI) simulation using a linear elastic material model with rigid wall CFD simulation in a realistic abdominal aortic aneurysm. They found that the rigid wall CFD simulation overestimated both the velocity magnitude and wall shear stress. Bonfanti et al. (2017) developed a patient-specific CFD multi-scale approach incorporating aortic wall compliance and applied it to study the hemodynamics of aortic dissection. The results indicated that the transmural pressure predicted by the compliant model was higher than that predicted by the rigid model. The systolic flow rate in the true lumen predicted by the compliant model was lower than that predicted by the rigid model, while the diastolic flow rate in the true lumen predicted by the compliant model was higher. Additionally, differences in the magnitude and oscillation of the wall shear stress were observed between compliant and rigid models (Qiao et al., 2019). Wall

compliance in aortic hemodynamics can be addressed using several approaches. For instance, Pant et al. (2014) proposed a lumped parameter method that introduced a capacitor before the inlet to account for FSI effects due to aortic compliance. Some studies have modeled the aortic wall as either linear or nonlinear (Alimohammadi et al., 2015; Bonfanti et al., 2018; Qiao et al., 2019; Kim et al., 2023), and isotropic or anisotropic (Jayendiran et al., 2018; Vignali et al., 2021; Wang et al., 2023) materials to perform FSI simulations. Additionally, based on aortic wall movements observed during clinical imaging, some researchers have utilized dynamic mesh methods (Ramiro et al., 2006; Midulla et al., 2012) or radial basis functions mesh morphing technology (Capellini et al., 2018; 2021; Calò et al., 2023) to perform FSI simulations. The impact of arterial wall elasticity on hemodynamic predictions varies significantly across different disease scenarios (Morab et al., 2024). Therefore, the influence of FSI simulations on the accuracy of aortic hemodynamics predictions requires further exploration. A comprehensive introduction to these FSI simulation approaches for hemodynamic predictions can be found elsewhere (Humphrey and Holzapfel, 2012; Hirschhorn et al., 2020; Athani et al., 2024).

3.5 Solution setup

Before performing CFD simulations, it is crucial to select the appropriate viscosity and turbulence models, as well as determine the time dependence and convergence criteria for the simulation.

The viscosity model characterizes the blood rheology. As a non-Newtonian fluid, the viscosity of blood varies with the shear rate. However, the assumption of Newtonian rheology is commonly adopted in hemodynamic studies because shear-thinning behavior is not significant in large arteries (Mutlu et al., 2023) and non-Newtonian simulations are more time-consuming (Liu et al., 2023). Qiao et al. (2019) compared the performance of a two-phase non-Newtonian model with the Newtonian model in predicting aortic dissection hemodynamics. They found that the Newtonian model might underestimate the magnitude of wall shear stress. However, Qiu et al. (2018) and Marrero et al. (2014) found that hemodynamic differences in aortic aneurysms due to the viscosity model were negligible. A comprehensive review of viscosity models for hemodynamic prediction can be found elsewhere (Yilmaz, 2008; Kannojiya et al., 2021).

The turbulence model is used to predict flow instability, which can be categorized based on the Reynolds number (Re) into laminar, transitional, and turbulent flow states. In straight, uniform tubes with steady flow, turbulence typically occurs when the Reynolds number exceeds the critical threshold of 2200 (Westerhof et al., 2019). However, for blood flow in the aorta, the pulsatile nature of the flow alters this threshold. Specifically, the descending phase of the cardiac cycle has been shown to facilitate the transition to turbulence (Winter and Nerem, 1984), while flow acceleration tends to have the opposite effect. The Womersley number (α), which quantifies the relative importance of inertial versus viscous forces, provides valuable insight into these oscillatory characteristics (Womersley, 1957). Nerem et al. (1972) confirmed that the occurrence of turbulence is related to both the peak Reynolds number (Re) and the Womersley number in an experimental

TABLE 1 Turbulence models used in aortic hemodynamic simulations.

Reference	Study object	Turbulence model
Xu et al. (2018)	Type-B aortic dissection	LES model
Martínez et al. (2023)	Ascending aorta	
Rezaeitalshmahalleh et al. (2024)	Abdominal aortic aneurysm	
Black et al. (2023)	Type-B aortic dissection	Standard k-omega turbulence model
Algabri et al. (2019)	Abdominal aortic aneurysm	SST k-omega turbulence model
Stokes et al. (2023a), Stokes et al. (2023b)	Type-B aortic dissection	
Kousera et al. (2013)	Healthy aorta	Transition SST turbulence model
Chi et al. (2017)	Type-A aortic dissection	
Cheng et al. (2014)	Type-B aortic dissection	
Cheng et al. (2015) Wan Ab Naim et al. (2018) Dai et al. (2020)		
Etli et al. (2021)	Thoracic aortic aneurysm	k-epsilon turbulence model
Moretti et al. (2023)	Aortic dissection	
Hohri et al. (2021)	Type-A aortic dissection	
Long Ko et al. (2017)	Type-B aortic dissection	
Botar et al. (2017)	Abdominal aortic aneurysm	
		Reynolds-stress model

study conducted in the canine ascending and descending aorta. As a result, hemodynamic studies typically assess the likelihood of turbulence based on the position of the inlet flow regime on the $R\epsilon$ - α diagram (Kousera et al., 2013). Additionally, some researchers suggest that the tortuous nature of arteries, along with sudden contractions or expansions at lesion sites, can also induce turbulence (Katz et al., 2023). Les et al. (2010) investigated aortic hemodynamics in eight patients with abdominal aortic aneurysms using direct numerical simulation (DNS). They observed that turbulence was primarily present distal to the aneurysm. DNS does not rely on assumptions about laminar or turbulent flow, making it particularly suitable for modelling transitional arterial flow. However, its high computational cost limits its widespread application in hemodynamic research. As alternatives, large eddy simulation (LES), eddy-viscosity models, and Reynolds-stress models are commonly employed for turbulence modelling in aortic hemodynamics, as summarized in Table 1. Among these models, the transition shear stress transport (SST) turbulence model is considered the most promising Reynolds-averaged Navier-Stokes model for predicting laminar-turbulent transition in large arteries (Tan et al., 2009; Kousera et al., 2013). Based on this turbulence model, Cheng et al. (2014) successfully predicted blood flow patterns that closely matched those measured using phase-contrast MRI in a patient with aortic dissection.

For time dependence, transient CFD simulations are commonly employed in hemodynamic studies to capture the pulsatile nature of blood flow accurately. However, these simulations can be time-intensive, which has prompted some researchers to explore alternative steady-state simulations. Qiu et al. (2018) found that in an abdominal aortic aneurysm model, the time-averaged wall

shear stress distribution in transient simulations closely matched that of steady-state simulations. Similar findings were reported by Chi et al. (2022) and Caballero and Lain (2015) for the thoracic aorta. Nonetheless, with the increasing availability of computational resources and advancements in parallel processing methods (Mirzaee et al., 2017; Hu et al., 2023), transient simulations have become the primary method for hemodynamic studies. These simulations allow for the calculation of various hemodynamic indicators over time, providing more comprehensive insights into flow dynamics. For transient simulations, the time step size plays a crucial role in the accuracy of predictions, as demonstrated in studies of IAs (Valen-Sendstad et al., 2013; Valen-Sendstad and Steinman, 2014; Dennis et al., 2017). Although similar investigations on the aorta are less common, it is recommended to perform a time-independence check before conducting transient simulations to ensure the accuracy of results.

Convergence criteria are also vital for ensuring that CFD simulations reach a valid endpoint. Dennis et al. (2017) found that a residual error of 10^{-5} for mass and momentum equations was sufficient for convergence in their IA model; however, this threshold may vary for different geometries. Additionally, for transient simulations, it is equally important to verify the statistical convergence of temporal indicators by comparing these values across at least two cardiac cycles (Poelma et al., 2015).

Several popular open-source and commercial CFD solvers are available for hemodynamic simulations (Azizi, 2023), with general-purpose software such as Ansys Fluent, Ansys CFX, COMSOL, OpenFOAM, and STAR-CCM+ being widely used. However, these general tools often require additional user programming to include specific cardiovascular functions, such as the Windkessel outlet

boundary. In contrast, cardiovascular-specific software, including SimVascular (Updegrave et al., 2017), CRIMSON (Arthurs et al., 2021), and DetecFluid (Liu et al., 2025), are more streamlined for hemodynamic applications as they already integrate these functions. Moreover, in-house developed codes are also used for specialized hemodynamic analyses, such as DNS for turbulence (Les et al., 2010).

3.6 Postprocessing and related metrics

Upon completing the numerical solutions, fundamental physical quantities like velocity and pressure are determined within the computational domain. From these quantities, various hemodynamic metrics are derived to analyze and characterize blood flow behavior. These metrics include flow pattern descriptors such as vorticity and helicity, energy-related parameters such as energy loss and pressure loss coefficient, and wall shear parameters like wall shear stress (WSS) and oscillatory shear index (OSI). Some of these metrics, initially proposed for arterial vessels other than the aorta, can be extended to other vascular regions due to shared underlying mechanisms. For instance, Shimogonya et al. (2009) introduced the gradient oscillatory number (GON) as a metric to assess the risk of IA initiation. GON can also be used to evaluate the risk of aortic aneurysms, as both the intracranial and aortic aneurysms share similar pathophysiological factors, such as endothelial dysfunction, inflammation, and remodeling of the arterial wall induced by hemodynamic factors (Tanweer et al., 2014; Signorelli et al., 2015; 2018; Gao et al., 2023). As such, a comprehensive summary of hemodynamic metrics relevant to both aortic and non-aortic diseases is provided in the [Supplementary Table S1](#) online.

Certain hemodynamic metrics exhibit strong correlations with one another. For example, Lee et al. (2009) found significant correlations between relative residence time (RRT) and time-averaged WSS (TAWSS) or OSI, suggesting that RRT might serve as a robust single metric for identifying low or oscillating shear regions. Additionally, metrics vary in their sensitivity to CFD settings. Lassila et al. (2020) demonstrated that although both OSI and transverse WSS (transWSS) can be used to assess the directional variation of the WSS vector, OSI is more sensitive to changes in blood flow dynamics in IAs. Consequently, transWSS performed better in assessing the risk of IA rupture. This highlights the importance of selecting appropriate metrics based on specific research goal and simulation settings.

In terms of data visualization during postprocessing, various graphic representations are commonly employed, including contour plots, vector plots, streamline plots, and isosurfaces of hemodynamic metrics. Postprocessing is often conducted at different levels of data granularity, with two main categories of focus. The first category is concerned with specific lesion sites, such as the rupture point of an aortic aneurysm (Teng et al., 2022) or the primary entry tear of an aortic dissection (Chi et al., 2017). The second category focuses on broader hemodynamic characteristics, such as the maximum, minimum, and average values of metrics within the aneurysm dome (Bappoo et al., 2021; Wen et al., 2023).

3.7 Validation

To ensure that CFD modelling accurately predicts the hemodynamic characteristics of the aorta, validation efforts are essential, though they can be complex and costly. CFD validation typically involves three approaches: *in vitro* validation using an idealized model (Mansouri et al., 2024), *in vitro* validation with a patient-specific model created through 3D printing (Ong et al., 2019; Bonfanti et al., 2020), and *in vivo* validation based on clinical measurements (Bonfanti et al., 2017; Bonfanti et al., 2019; Boccadifuoco et al., 2018; Stokes et al., 2021). Table 2 provided a summary of these validation studies related to aortic hemodynamics, highlighting CFD settings, validation methods, validated parameters, and key findings. Among these methods, *in vivo* validation against clinical data is considered the most reliable way to confirm CFD accuracy. Typically, clinical studies utilize invasive blood pressure measurements taken by arterial catheter (Bonfanti et al., 2019), blood flow rates obtained via phase-contrast MRI (Bonfanti et al., 2017), and cross-sectional velocity profiles captured by 4D-flow MRI (Stokes et al., 2021) as reference values. However, other hemodynamic metrics, such as WSS, are more difficult to validate due to limitations in the temporal and spatial resolution of current measurement techniques (Miyazaki et al., 2017).

Furthermore, some validation studies have investigated the impact of CFD modelling settings on prediction accuracy. Boccadifuoco et al. (2018) compared the performance of rigid and compliant vessel wall models in predicting the hemodynamic characteristics of the thoracic aorta. By comparing their results with *in vivo* phase-contrast MRI data, they found that FSI simulations with a compliant wall yielded more accurate flow velocity predictions. The role of FSI simulations on the accuracy of hemodynamic predictions across various disease states requires further exploration (Morab et al., 2024). Additionally, Black et al. (2023) studied how parameters in three-element Windkessel models at the outlets affect the predicted flow rate waveforms. Their findings showed that using parameters calibrated with flow waveforms from 4D-flow MRI data resulted in more accurate predictions.

4 Studies and limitations

The primary goal of hemodynamic prediction is to establish a link between hemodynamic metrics and aortic diseases and their related complications. This understanding can inform better clinical management strategies. We conducted a systematic search to investigate the application of hemodynamic prediction in aortic aneurysm and dissection. A full description of the search and screening strategy can be found in the [Supplementary Material](#) online. To ensure a reliable connection between hemodynamics and aortic diseases, we focused on studies with sample sizes greater than five, including 17 studies on aortic aneurysms and 9 studies on aortic dissections.

Accurate correlation between hemodynamic features and diseases requires careful study design. Common methods used in these studies include virtual repair, longitudinal analysis, and parallel control (Peiffer et al., 2013). Virtual repair is often used to identify risk factors associated with the occurrence of aortic diseases. However, due to the complex shape changes resulting

TABLE 2 Summary of validation studies on aortic hemodynamics.

Reference	Study object and geometry model	CFD settings	Validation methods, validated parameters, and major findings
Mansouri et al. (2024)	Healthy thoracic aorta; idealized aorta with major anatomic features	Steady-state, k-omega turbulence model, Newtonian fluid, rigid wall, uniform bulk velocity at inlet, zero-pressure outlet	PIV experiments; velocity and flow patterns. The global flow patterns in the idealized model showed excellent qualitative and quantitative agreement between CFD simulations and PIV experiments.
Ong et al. (2019)	Thoracic aortic aneurysm; patient-specific model	Transient, laminar, Newtonian fluid, compliant wall with linear elastic material, time-dependent flow profile at inlet, pressure waveform at outlet	PIV experiments; flow at inlet, pressure at outlets, and flow pattern. Flow behaviors observed in FSI simulations closely matched those in experiments.
Bonfanti et al. (2020)	Type B aortic dissection; patient-specific model	Transient, SST k-omega turbulence model, Newtonian fluid, rigid wall, flow rate waveform at inlet, three-element Windkessel model at outlet	PIV experiments; flow rate and pressure at inlet and outlets, velocity, flow patterns. Numerical results on flow rate, pressure, and velocity fields closely matched experimental data.
Bonfanti et al. (2017)	Type B aortic dissection; patient-specific model	Transient, laminar, non-Newtonian fluid (Carreau-Yasuda model), compliant wall (moving boundary method), uniform velocity profile at inlet, three-element Windkessel model at outlet	2D phase-contrast MRI; flow rate at different locations along the aorta, displacement of the vessel wall. CFD simulations underestimated peak flow rates, but accurately predicted flow waveforms and vessel wall displacement.
Miyazaki et al. (2017)	Healthy aortic arch and double aortic arch; patient-specific model	Transient, laminar or LES or k-epsilon model, Newtonian fluid, rigid wall, flow rate waveform at inlet, pressure waveform at outlet	4D-flow MRI; velocity, flow patterns, WSS distribution, energy loss. CFD simulations accurately predicted flow patterns distal to the aortic arch but failed to capture helical flow in the ascending aorta. WSS distribution matched MRI results, though the average WSS was five times higher, likely due to MRI's low spatial resolution.
Boccadifuoco et al. (2018)	Healthy thoracic aorta; patient-specific model	Transient, laminar, Newtonian fluid, rigid or compliant wall (linear elastic material), flow rate waveform at inlet, three-element Windkessel model at outlet	4D-flow MRI; flow rate waveform at outlets, vessel wall displacement, velocity fields. CFD simulations showed discrepancies with measured results, particularly in the aortic arch and descending aorta. Using a lower Young's modulus improved accuracy but tended to significantly underestimate peak flow rate.
Bonfanti et al. (2019)	Type B aortic dissection; patient-specific model	Transient, laminar, non-Newtonian fluid (Carreau-Yasuda model), rigid wall with a capacitor before the inlet to account for FSI effects, flow rate waveform at inlet, three-element Windkessel model at outlet	Invasive blood pressure measurements by catheter; pressure in the true and false lumen along the aorta. CFD predictions closely matched invasive catheter measurements.
Stokes et al. (2021)	Healthy thoracic aorta; patient-specific model	Transient, SST k-omega turbulence model, rigid wall or compliant wall (moving boundary method), flow rate waveform at inlet, three-element Windkessel model at outlet	Cine-MRI and 4D-flow MRI; flow rate waveform, luminal cross-sectional area variation, velocity, flow patterns. Simulated luminal area and flow rate variations closely matched clinical measurements. Compliant and rigid simulations over- and under-predicted peak flow rates, while velocity profiles showed moderate consistency with 4D-flow MRI data.

from aortic aneurysms or dissections, there is still a lack of efficient, automated technology for repairing and modelling a healthy aorta. Longitudinal analysis is frequently employed to link hemodynamic metrics with disease progression. However, this approach is limited by the potential radiation exposure associated from clinical imaging. Parallel control offers the greatest flexibility and is applicable to all stages of aortic diseases, but it typically requires a large sample size to minimize the impact of intra-group differences.

Despite the increasing body of research on aortic hemodynamics, these findings have yet to be widely applied in clinical settings. We will examine the current barriers to implementing aortic hemodynamic models in clinical practice.

4.1 Aortic aneurysm

This review includes 17 studies on aortic aneurysms published between 2010 and 2024, detailed in the [Supplementary Table S2](#) online.

Of these, 14 studies focused on abdominal aortic aneurysms (AAA) and three on thoracic aortic aneurysm. The primary objective of these studies was to investigate the relationship between aneurysm volume expansion (Joly et al., 2020; Meyrignac et al., 2020; Bappoo et al., 2021; Rezaeitalshmahalleh et al., 2024), progression (Arzani et al., 2014; Zambrano et al., 2016; McClarty et al., 2022; Salmasi et al., 2023), rupture (Boyd et al., 2016; Chisci et al., 2018; Qiu et al., 2019; 2022; Zhou et al., 2021; Teng et al., 2022), and hemodynamic characteristics. Additionally, the effects of physiological factors such as exercise (Les et al., 2010; Suh et al., 2011) and hypertension (Ramaekers et al., 2024) on these hemodynamic features were explored.

The methodologies employed in these studies included parallel control (12 studies) and longitudinal analysis (5 studies), either alone or in combination. The most common imaging technique was CTA (10 studies), followed by MRA (4 studies). Two studies used 4D-flow MRI, which allowed for the simultaneous acquisition of patient-specific inlet velocity profiles. One study adopted CECT for AAA imaging. Most studies modeled blood flow as a Newtonian

fluid (12 studies) and assumed laminar flow (7 studies), with 14 studies conducting transient simulations. Regarding the boundary conditions, only one study modeled the vessel wall as a nonlinear, isotropic, hyperelastic material for FSI analysis (Teng et al., 2022), while the rest used a rigid, no-slip wall. For inlet boundary conditions, six studies used patient-specific, clinically measured flow rates, while the others relied on empirical values. At the outlets, nine studies applied three-element Windkessel models, while the remainder utilized empirical pressure values (5 studies) or flow distributions (1 study). In the postprocessing of hemodynamics, the most commonly assessed metrics were WSS, TAWSS, OSI, RRT, and endothelial cell activation potential (ECAP).

Three studies on aneurysm volume expansion confirmed a strong correlation between low baseline WSS and AAA expansion (Joly et al., 2020; Meyrignac et al., 2020; Bappoo et al., 2021). Furthermore, Joly et al. (2020) found that lower minimum TAWSS, along with higher RRT and ECAP values, were linked to a higher risk of rapid AAA expansion.

Two studies on intraluminal thrombus (ILT) progression in AAA yielded conflicting results. Arzani et al. (2014) found that low OSI was the primary factor associated with ILT growth, while low TAWSS showed no significant role in thrombus deposition. In contrast, Zambrano et al. (2016) identified low WSS as a key driver of ILT accumulation. These differences may stem from varying thresholds for low WSS. Arzani et al. (2014) considered WSS below 0.1 Pa as low, while Zambrano et al. (2016) identified the lowest TAWSS in their study at around 0.4 Pa. Despite these discrepancies, both studies agreed that thrombus deposition primarily occurred in recirculation zones.

Two studies on ascending thoracic aortic aneurysm progression found that elevated WSS was associated with local biomechanical deterioration (McClarty et al., 2022; Salmasi et al., 2023). In addition, Salmasi et al. (2023) suggested that a large angle between the left ventricular outflow tract and ascending aorta may contribute to the abnormal elevation of WSS.

Five of the six studies on AAA rupture showed that low WSS could distinguish aneurysms at high risk of rupture or predict rupture locations (Boyd et al., 2016; Chisci et al., 2018; Qiu et al., 2019; Zhou et al., 2021; Teng et al., 2022). Although Qiu et al. (2022) did not find significant differences in WSS values between ruptured and unruptured aneurysms, they observed a larger area of low WSS in the ruptured group. They also identified that a non-physiological flow pattern, characterized by a helical main flow channel with vortices, strongly associated with rupture risk. In addition, ILT deposition, which generally occurs in areas of blood recirculation (Boyd et al., 2016), was linked to rupture risk. Studies suggested that thin-layered ILT might offer a protective effect, while thick-layered ILT was considered a risk factor for rupture (Qiu et al., 2019; Zhou et al., 2021).

4.2 Aortic dissection

Nine studies on aortic dissections published between 2013 and 2023 were included, as detailed in the Supplementary Table S3 online. Of these, six studies were on TBAD and three on type A aortic dissection (TAAD). These studies mainly focused on the relationship between tear occurrence and hemodynamic characteristics (Chi et al., 2017; Hohri et al., 2021; Marrocco-Trischitta and Sturla, 2022; Wen

et al., 2022; Wen et al., 2023; Williams et al., 2022; Li et al., 2023), as well as the correlation between hemodynamics and disease progression (Cheng et al., 2013; Shang et al., 2015).

All studies used parallel control methodology, with three incorporating longitudinal analysis and three combined virtual repairs. Seven studies used CTA imaging, while two studies adopted CECT for TAAD imaging. All studies performed transient simulations. In six studies, blood was modeled as a Newtonian fluid, whereas turbulence models were employed in three studies, and laminar flow was assumed in two others. For boundary conditions, all studies simplified the vessel wall as rigid and no-slip. Empirical flow waveforms were specified at inlet in all cases. At the outlet, four studies used three-element Windkessel models, while the rest utilized empirical pressure values. In the postprocessing of hemodynamic characteristics, the most commonly assessed metrics were WSS, TAWSS, OSI, and local normalized helicity (LNH).

Four studies on TBAD occurrence found a correlation between abnormal flow patterns, disturbed WSS, and tear location (Marrocco-Trischitta and Sturla, 2022; Wen et al., 2022; Wen et al., 2023; Li et al., 2023). These studies suggested that disrupted helical flow in the proximal descending aorta contributed to the initial tear formation. Additionally, metrics of WSS disturbance, such as transWSS (Li et al., 2023), cross-flow index (CFI) (Wen et al., 2022; Wen et al., 2023), and OSI (Wen et al., 2023), were significantly elevated in TBAD patients compared to healthy individuals. In TAAD, two studies linked elevated maximum WSS in the ascending aorta to an increased dissection risk (Chi et al., 2017; Williams et al., 2022). However, Hohri et al. (2021) found high OSI, rather than high WSS to be more closely associated with the tear location.

Two studies on TBAD progression suggested that higher flow rates in the false lumen were associated with both short- and long-term adverse outcomes, including malperfusion and rapid aneurysmal dilation (Cheng et al., 2013; Shang et al., 2015). Cheng et al. (2013) found that the flow rate in the false lumen correlated with the size and location of the primary entry tear, while Shang et al. (2015) observed a significant link between elevated TAWSS and aneurysmal dilation.

4.3 Limitations

Obviously, the studies included a limited number of patients, with a total of 1,047 subjects across 26 studies, the largest of which involved 295 subjects (Bappoo et al., 2021). Notably, 80% of the studies had fewer than 50 patients. Additionally, due to ethical concerns, it is difficult to track the severe progression of aortic aneurysms or dissections, which results in smaller patient cohorts for these conditions, making it harder to fully understand the role of hemodynamics. As an example, we can refer to the noninvasive fractional flow reserve, a hemodynamic indicator that has been used clinically to diagnose coronary stenosis. Prospective studies on this indicator, like the DISCOVER-FLOW study (Koo et al., 2011) and the DeFACTO study (Nakazato et al., 2013), involved over 100 patients and more than 400 vessels. However, given that the aorta is far more complex than the coronary arteries, larger patient cohorts will be necessary to establish a clear relationship between hemodynamics and disease progression in aortic conditions.

Additionally, many studies did not provide comprehensive descriptions of the parameters used in their CFD models, as summarized in [Supplementary Tables S1, S2](#). Only five studies fully detailed their settings ([Cheng et al., 2013](#); [Qiu et al., 2019](#); [Joly et al., 2020](#); [Ramaekers et al., 2024](#); [Rezaeitaleshmahalleh et al., 2024](#)). Although this does not necessarily undermine the reliability of these studies, it does limit the applicability of their findings to other cohorts.

Moreover, patient-specific boundary conditions were seldom used, with only six studies employing clinically measured inlet flow waveforms. Although the use of empirical boundary conditions may compromise the accuracy of CFD models in reflecting true aortic hemodynamics, such simplifications can still be acceptable if they do not affect disease stratification, as demonstrated in studies on intracranial aneurysms ([Li et al., 2020](#)).

Finally, advanced modelling techniques were rarely employed in these large sample studies, likely due to the challenges of implementation and the substantial computational time required. For instance, most studies assumed a rigid, no-slip vessel wall, with only one study using a compliant wall for FSI simulations ([Teng et al., 2022](#)). However, rigid wall models fail to capture certain clinical features such as dynamic obstruction caused by intimal flap motion in aortic dissection ([Kim et al., 2023](#)). This highlights the need for further development and application of advanced modelling approaches in diverse clinical scenarios, focusing on reducing implementation complexity and improving overall performance.

5 Future directions

Despite the challenges associated with CFD modelling, such as complex computational processes and high computational demands, it shows considerable promise in the clinical management of cardiovascular diseases. However, significant uncertainties remain in accurately predicting the hemodynamics in aortic aneurysms and dissections. While existing studies have provided guidance on parameter settings for specific stages of CFD modelling, these insights remain insufficient for the full modelling process. Future research should focus on assessing the impact of different parameter settings on risk stratification through large-scale studies and provide well-founded recommendations.

Several large sample studies have demonstrated consistent associations between hemodynamics and aortic diseases, highlighting the potential of CFD-based hemodynamic analysis in clinical management. However, these studies are often constrained by limited sample sizes and insufficient detail on CFD parameters, such as turbulence model and convergence criteria. To address these limitations, future research should prioritize expanding cohort sizes and establishing standardized reporting protocols for computational modelling details.

This review outlines the workflow in CFD modelling for aortic hemodynamics and highlights recent advancements in the field. It also examines large sample studies to explore the relationship between hemodynamic features and aortic aneurysms and dissections. Our hope is to contribute to advancing the clinical application of CFD-based hemodynamic analysis in the management of these conditions.

Author contributions

MH: Conceptualization, Data curation, Formal Analysis, Investigation, Methodology, Writing—original draft. BC: Funding acquisition, Project administration, Resources, Writing—review and editing. YL: Formal Analysis, Project administration, Supervision, Writing—review and editing.

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Conflict of interest

Author MH was employed by Boea Wisdom (Hangzhou) Network Technology Co., Ltd.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

The Supplementary Material for this article can be found online at: <https://www.frontiersin.org/articles/10.3389/fbioe.2025.1556091/full#supplementary-material>

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Glossary

CFD	computational fluid dynamics
TBAD	type B aortic dissection
DSA	digital subtraction angiography
CECT	contrast-enhanced computed tomography
CTA	computed tomography angiography
MRI	magnetic resonance imaging
MRA	magnetic resonance angiography
3DRA	3D rotational angiography
IA	intracranial aneurysm
FSI	fluid-structure interaction
Re	Reynolds number
α	Womersley number
Rê	peak Reynolds number
DNS	direct numerical simulation
LES	large eddy simulation
SST	shear stress transport
WSS	wall shear stress
OSI	oscillatory shear index
GON	gradient oscillatory number
RRT	relative residence time
TAWSS	time-averaged wall shear stress
transWSS	transverse wall shear stress
AAA	abdominal aortic aneurysm
ECAP	endothelial cell activation potential
ILT	intraluminal thrombus
TAAD	type A aortic dissection
LNH	local normalized helicity
CFI	cross-flow index