Highlights

Sailing Forward: A Review of Contrasts and Synergies Between Racing and Robotic Sailing

Yang An, Jean-Baptiste R. G. Souppez, Zhikang Ge, Bo Peng, Mengwei Zhang, Gaofei Xu, Zhengru Ren

- First cross-domain review of racing vs robotic sailing across technical dimensions
- Four-domain state-of-the-art method compendium with comparative usage analysis
- Explains drivers of divergence and maps technical transferability and barriers
- Identifies shared challenges and proposes a collaboration-oriented research agenda

Sailing Forward: A Review of Contrasts and Synergies Between Racing and Robotic Sailing

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Abstract

Sailing has profoundly influenced human history; however, in the modern era, wind-driven navigation has bifurcated into two primary domains: competitive racing and autonomous robotic sailing. While both are governed by the same underlying physical principles, their divergent operational objectives have resulted in isolated research communities and distinct design philosophies. This disciplinary divide has impeded cross-pollination, leaving a significant void in systematic comparative analyses between the two fields. To bridge this gap, this paper leverages cross-domain expertise to provide a comprehensive, perspective-driven synthesis that explicitly compares racing and robotic sailing. We trace their historical divergence and contrast their platforms, objectives, and core technical emphases. The analysis adopts a hierarchical structure across four technical dimensions: component performance evaluation provides the foundation for overall performance modeling, which in turn supports motion control strategies and informs high-level decision-making, such as reactive navigation and weather-aware routing. By applying a structured five-metric framework, we evaluate the transferability of specific methodologies across these themes and identify the principal technical obstacles. Our findings reveal critical synergies, fundamental divergences, and shared challenges, ultimately highlighting strategic opportunities for mutual advancement within the broader wind-propulsion community.

Keywords:
Sailing, Racing sailboats, Autonomous sailboat, Comparative review

1. Introduction

1.1. Historical context

Driven by the perpetual power of the wind, sailboats rank among the most transformative inventions in human history, often compared in significance to the wheel [1]. Since their origins in the 7th millennium BC Aegean [2] and 6th millennium BC Persian Gulf [3], sailboats have facilitated global trade, cultural exchange, and naval exploration [4]. This technology reached its zenith during the "Age of Exploration" (15th–19th centuries), powering scientific discovery and geopolitical transformation [5]. Although later displaced by steamships in commerce [6], the legacy of sailing has evolved through modern reinterpretation along two research trajectories: racing and robotic sailing.

Racing sailboats generally trace their organized competition to the 16th-century Netherlands, propelled by vibrant maritime trade [7]. Over time, flagship events such as the America's Cup (1851) and Olympic sailing (1900) have formalized the sport as a major technological driver [8, 9]. A sustained quest for fairness and victory catalyzed the evolution of yacht ratings, from early 19th-century handicapping systems [9, 10, 11, 12] to modern systems [13, 14, 15, 16] capable of evaluating advanced appendages [17, 18] and weather variations [19]. Parallel to

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this, competitive pressure spurred a series of multidisciplinary breakthroughs [20, 21], such as high-modulus composites since the 1960s [22, 23], the mainstreaming of velocity prediction program (VPP) [24, 25, 26] and computational fluid dynamics (CFD) simulation workflows [27, 28] in the 1990s, and the adoption of canting keels originating in the late 1950s [29, 30]. Most prominent is the recent foiling revolution, extending from the pioneering *L'Hydroptère* [31] to the AC72 [32, 33] and AC75 [34, 35, 36] classes. These advancements reflect a design philosophy centered on maximizing power-to-weight ratios under human-in-the-loop control.

Sailing robots (or autonomous sailboats) serve as specialized platforms for oceanographic observation, with an evolution framed in three stages: emergent (1968–2004), developmental (2005–2018), and application (2019–present) [37]. The emergent phase, epitomized by the SKAMP concept [38] and the *Atlantis* prototype [39, 40], was primarily constrained by sensing, control, and regulatory limitations [41]. The developmental phase was catalyzed by community benchmarks such as the Microtransat Challenge and the World Robotic Sailing Championship [42, 41], delivering credible operations by *Sailbuoy* [43, 44] and *Saildrone* [45], and culminating in the first autonomous transatlantic crossing in 2018 [46]. Since 2019, growing interest from agencies such as the National Oceanic and Atmospheric Administration, the Defense Advanced Research Projects Agency, and Lockheed Martin [47] has driven a strategic shift toward the operationalization, upscaling, and militarization of autonomous sailboats. This trend is exemplified by autonomous maritime observation missions conducted in extreme weather conditions [48, 49], the upscaling to the 22-meter *Saildrone Surveyor* [50], and an overall move toward security-oriented applications [51]. Consequently, ongoing development now prioritizes performance-informed evaluation [52, 53], energy and structural endurance [54, 55], and multi-vessel coordination [56] to support these persistent, large-scale missions.

1.2. Motivation for an integrative review

Although both rely on wind propulsion, the two research domains pursue different objectives and are studied largely within distinct academic communities. Racing sailing research seeks to develop high-performance vessels optimized for competitive regattas under explicit class rules and event constraints. By contrast, robotic sailing aims to achieve robust, long-duration autonomy for oceanographic observation in unstructured and dynamic marine environments.

In terms of research communities, robotic sailing is led by specialists in robotics, control, and autonomous systems, with publications appearing in robotics, control, and ocean engineering outlets; by contrast, racing sailing is driven by sailors, naval architects, and specialists in aerodynamics and hydrodynamics. Foundational results often circulate within relatively insular communities, and some findings are kept proprietary for competitive reasons. This separation limits sustained academic dialogue between the two communities.

Yet the physical principles are shared, and techniques developed in one domain often have clear potential in the other. Examples include design optimization strategies [57, 58], dynamic modeling of sails, foils, and hulls [59, 60], control and decision-making [61, 62], and sensor development and integration [63, 64, 65]. In practical terms, robotic sailing researchers seek actionable knowledge of sailboat aerodynamics and hydrodynamics, together with methods matured in the racing community that can be reused with minimal adaptation. Conversely, deeper engagement with robotics and algorithmic expertise can help research outputs from the racing community reach broader audiences and inspire new lines of inquiry beyond established conventions. A wider readership may also benefit, notably wind-assisted ship propulsion researchers who combine specialist sailing design and performance knowledge [66, 67] with algorithmic approaches akin to robotic sailing [68].

Recognizing this largely untapped potential, the authors, drawing on backgrounds in both robotics and racing, set out to bridge the disciplinary gap between the two domains. As an expert-led synthesis and perspective review, this work constitutes, to the best of the authors' knowledge, the first comprehensive effort to bridge racing and robotic sailing research. By juxtaposing methods and practices across the two domains, the review provides an intuitive yet systematic account of where their concerns diverge, why those differences arise, and which factors hinder or enable the transfer of methodologies between them.

1.3. Scope of this review

Our sources primarily include journals such as the *Journal of Sailing Technology*, the *IEEE Transactions* series, *Ocean Engineering*, *Applied Ocean Research*, and the *Journal of Marine Science and Engineering*, together with proceedings from *the International Robotic Sailing Conference*, *the Chesapeake Sailing Yacht Symposium*, *High*

Performance Yacht Design, and *Innov'Sail* as well as selected online resources that document sailing technology development, race tactics, class rules, technical bulletins, and related updates.

We do not provide a fully reproducible, keyword-driven search and screening protocol because the two domains are indexed asymmetrically. Robotic sailing is well covered in major databases and already supports topic-specific bibliometric analyses [69]. By contrast, much of the influential racing literature appears in community venues [70, 71, 72, 73, 74, 75] that are not indexed by services such as Web of Science. Although the racing community generously allowed us to consult otherwise inaccessible archival proceedings and technical reports, the lack of indexing means we cannot apply established bibliometric tools or assemble a complete, reproducible corpus from database searches alone.

Accordingly, selection relied on the authors' complementary expertise across robotic and racing sailing. Inclusion prioritized works that are representative or formative for each topic and that illuminate historical development and the current state of the art. We do not claim completeness; rather, we aim for an unbiased, balanced, and well-evidenced synthesis.

1.4. Roadmap of this review

The remainder of the paper is structured as follows. Section 2 introduces key platform types and application contexts, highlighting the distinct operational settings and design philosophies of racing and robotic sailing, so that readers from both communities can readily apprehend their differences.

Sections 3—6 examine four hierarchical technical dimensions: component performance evaluation (Section 3), which underpins overall vessel modeling (Section 4); these models support control strategy development (Section 5), which, in turn, enables high-level reactive navigation and weather routing (Section 6). Each of these sections follows a common template: *Central issues* outline the fundamental questions faced by the topic; *Methodologies* survey the state of the art; *Contrasts and convergences* clarifie how the two domains differentially employ these methods; and *Synthesis and transferability analysis* evaluates the cross-domain migration of specific methodologies.

To provide a structured mapping of cross-domain transferability, each technical dimension is evaluated against five consistent metrics: *potential for transfer* assesses the alignment of primary objectives and constraints to determine the degree of methodological reusability; *maturity leader* identifies the domain possessing superior methodological rigor or a more extensive research volume; *main beneficiary* denotes the field poised to gain most from technology overflow, manifested as overcoming inherent conceptual limitations or a significant reduction in the resources required for de novo methodological development; *current level of transfer* reflects the extent of existing adoption, ranging from conceptual inspiration to direct, routine application; and *main obstacles* highlight the critical bottlenecks, such as data scarcity or the absence of key enabling technologies.

Section 7 synthesizes the analysis across dimensions, identifying shared challenges and research opportunities. Finally, Section 8 concludes by summarizing the contributions and implications of this review.

2. Application Contexts and Platform Characteristics

Sailing vessels function at the interface of two fluids, namely air and water, and thus rely on a complex integration of aerodynamic and hydrodynamic systems for efficient propulsion, stability, and control. Their core structure consists of three interdependent subsystems:

- **Sails**:

  Sails are the primary aerodynamic components that harness wind energy for forward propulsion. They also generate lateral forces and heeling moments, fundamentally influencing the vessel's balance and maneuverability. Their aerodynamic performance depends on shape, trim, and wind interaction, which must be dynamically adjusted to maintain propulsion efficiency under varying conditions. Effective sail control requires balancing lift, drag, and stability, making sails central to both performance and control strategies.

- **Canoe Body**:

  The canoe body is the main hydrodynamic structure, providing buoyancy and contributing to righting moments that counteract heeling. Its geometry affects wave resistance, wetted surface area, and motion response, thus

(a) IMOCA 60 with canting keel and surface-piercing foils for offshore racing, adapted from [76]

(b) Hydrofoiling International Moth for inshore competition, adapted from [77]

(c) Saildrone with spindle hull for autonomous ocean observation, adapted from [78]

Figure 1: Platforms in racing and robotic sailing.

influencing both efficiency and seakeeping. It also houses structural reinforcements, onboard systems, and payloads essential for long-term operation.

- **Appendages**:

  Appendages include all hydrodynamic components beyond the canoe body, primarily the keel, rudder, and, in some cases, hydrofoils. The keel resists lateral aerodynamic forces and enhances directional stability. The rudder governs yaw control for precise maneuvering. Hydrofoils, used in high-performance vessels, provide dynamic lift to reduce drag and improve speed, and provide dynamic stability, though their complexity often limits their applicability in robustness-critical designs.

Although sailing vessels, be they racing or robotic, are constructed from similar subsystems, their platform characteristics vary markedly depending on intended usage. This study adopts a functional classification scheme, grouping platforms into three representative categories: ocean-going yachts, inshore dinghies (both of which fall within the broad classification of racing sailboats, differing primarily in scale and deployment areas), and autonomous sailboats, as shown in Figure 1.

2.1. Ocean-going yachts

Ocean-going yachts are medium- to large-scale crewed sailing platforms built for long-distance oceanic competition. Typical applications include races such as the Vendée Globe and the Volvo Ocean Race, where vessels operate in restricted open-sea environments along predefined fixed checkpoints. The large spacing between them permits tactical flexibility based on wind and current conditions. A representative example is the International Monohull Open Class Association (IMOCA) 60 (Figure 1a), which measures 18.28 meters and displaces 8.5 tons.

These vessels use soft sails in multi-sail configurations. In addition to the mainsail, they employ a wide range of headsails and complementary sails, such as jibs, genoas, code Zeros, asymmetric and symmetric spinnakers, and storm sails, deployed to maintain optimal propulsion across changing wind conditions. Sail trim and transitions are managed dynamically by the crew to balance performance, safety, and stability. The canoe bodies are typically wide and voluminous to enhance form stability. Stability is further augmented by deep, heavy fixed keels, or alternatively by canting keels, which shift laterally to increase righting moments with minimal hydrodynamic penalty. Some yachts also feature surface-piercing hydrofoils to reduce drag and improve lift at speed, as well as provide dynamic stability [79].

To alleviate crew workload, particularly on solo or short-handed ocean-going yachts, modern vessels often integrate mechanical aids such as wind-vane steering alongside advanced autopilot systems. These technologies can maintain a stable heading under varying wind and sea conditions, and often exceed manual steering in terms of endurance and consistency. Nonetheless, critical tasks such as sail trim, route planning, and tactical decision-making remain reliant on human input, as competitive success continues to depend on real-time judgment and situational adaptation.

2.2. *Inshore dinghies*

Inshore dinghies are small, lightweight crewed platforms optimized for short-course competitive racing in enclosed or semi-enclosed waters. Courses typically consist of fixed buoy sequences with constrained route flexibility, placing a strong emphasis on real-time maneuvering and close-quarters tactical interactions. A representative example is the International Moth, depicted in Figure 1b, with a length of 3.36 m and a mass of 26 kg.

Dinghies typically employ a mainsail and a jib, supported by stays and rigging hardware to maintain structural tension and control; some classes include a spinnaker [80], while others are limited to a mainsail only [81]. The canoe bodies are narrow and lightweight to maximize speed and maneuverability. Rather than employing heavy keels, dinghies rely on retractable centerboards to provide hydrodynamic side force. Due to the absence of fixed ballast stability, sailors actively generate righting moments by shifting their body position, often through hiking or trapezing. Some modern dinghies, such as the Moth, incorporate hydrofoils capable of lifting the canoe body entirely out of the water at speed, significantly reducing drag and increasing velocity.

All sail and steering functions are manually controlled. Dinghy sailing demands frequent, fine-grained interventions at short time scales: the sailor must simultaneously manage tiller input, sail trim, body position (hiking/trapezing), and, where applicable, foil angle, while continuously responding to wind shifts, gusts, waves, and nearby traffic. This yields a highly interactive and physically intensive style in which performance is tightly coupled to sailor skill and rapid situational decision-making.

Although raced inshore, high-performance America's Cup craft (e.g., AC75) are excluded from this subsection. Unlike dinghies, these are yacht-scale foiling platforms that require professional, precise flight control and shore support. Their narrow operating envelopes render them unsuited to open-ocean survival or long-duration operations.

2.3. *Autonomous sailboats*

Autonomous sailboats (Figure 1c) are uncrewed platforms primarily designed for long-endurance ocean observation. They can operate in remote or hazardous marine environments where human presence is impractical or unsafe. Unlike racing sailboats, their navigation is mission-driven and dynamically adjusted, without reliance on fixed courses or predefined checkpoints. Most platforms prioritize safety and compactness, typically measuring less than 5 meters in length and displacing under 500 kg [82].

For improved durability and ease of control, most autonomous sailboats adopt wingsails. These vessels adopt a wide range of canoe body geometries, from conventional monohulls to unconventional spindle-shaped designs, selected to balance seakeeping performance, payload capacity, and construction simplicity. Regardless of form, they generally incorporate deep, heavily ballasted fixed keels that provide sufficient righting moments to operate reliably under strong winds and large heeling forces, without requiring active correction.

All core functionalities, sail trimming, steering, and navigation, are executed autonomously by onboard control systems. To maintain robust performance amid dynamic wind and current conditions, these controllers typically operate at high update rates. As long-endurance missions are energy-limited, power consumption becomes a key design driver, constraining actuation duty cycles, sensor sampling, and decision-making frequency. Human involvement is generally limited to issuing high-level mission commands and remotely monitoring system status via satellite links.

2.4. *Summary and comparison*

A consolidated comparison of the three platform types is presented in Table 1. From a cross-domain perspective, autonomous sailboats should not be regarded as miniaturized versions of any specific racing class. Interestingly, given that their length and mass fit between racing yachts and dinghies, much of the design methodology and performance analysis derived from both crewed classes can be adapted to autonomous platforms.

In terms of operational environment, autonomous sailboats function in the most unstructured and hazardous maritime conditions. Their canoe body and keel configurations more closely resemble those of ocean-going yachts, relying primarily on passive stability to withstand large heeling moments without active correction. However, in terms of physical scale, they align more closely with inshore dinghies; both are small, lightweight platforms that demand high-frequency actuation, whether through manual or autonomous control.

Table 1: Contrasts among sailing platform categories

Category	**Ocean-going yachts**	**Inshore dinghies**	**Autonomous sailboats**
Primary objective	Long-distance racing	Short-course racing	Long-term observation
Environment	Restricted open sea	Semi-enclosed waters	Remote open sea
Route flexibility	Fixed checkpoints	Predefined buoy courses	Mission-centric
Typical length	6.5–20 m	2–5 m	<5 m
Typical displacement	1–10 t	20–150 kg	5–500 kg
Sail type	Multi-sail configuration	Mainsail and jib	Wingsail
Canoe body	Wide and voluminous	Narrow and lightweight	Varied designs
Keel type	Deep or canting keel	Light centerboard	Deep fixed ballast keel
Stability source	Passive and active	Active only	Passive only
Advanced appendages	Surface-piercing foils	Fully submerged foils	No foils
Demand for autonomy	Autopilot-assisted	Fully manual	Fully autonomous

Unlike crewed sailing platforms, autonomous sailboats are free from class rules and racecourse constraints, enabling hull and rig designs that prioritize capsize resistance, robustness, and general-purpose operability across diverse and uncertain marine conditions.

System-wise, the absence of onboard crew precludes the use of complex mechanisms such as multi-sail switching or furling systems. Instead, autonomous sailboats typically adopt simplified and robust solutions, most notably rigid wingsails, that support consistent automated operation. While energy management is not the focus of this paper, it remains a fundamental consideration that implicitly shapes system configuration.

In summary, autonomous sailboats exhibit distinctive characteristics that set them apart from both ocean-going yachts and inshore dinghies. In the following sections, we examine these distinctions through four key perspectives: component performance evaluation, overall performance evaluation, motion control, and reactive navigation and weather routing.

3. Component Performance Evaluation

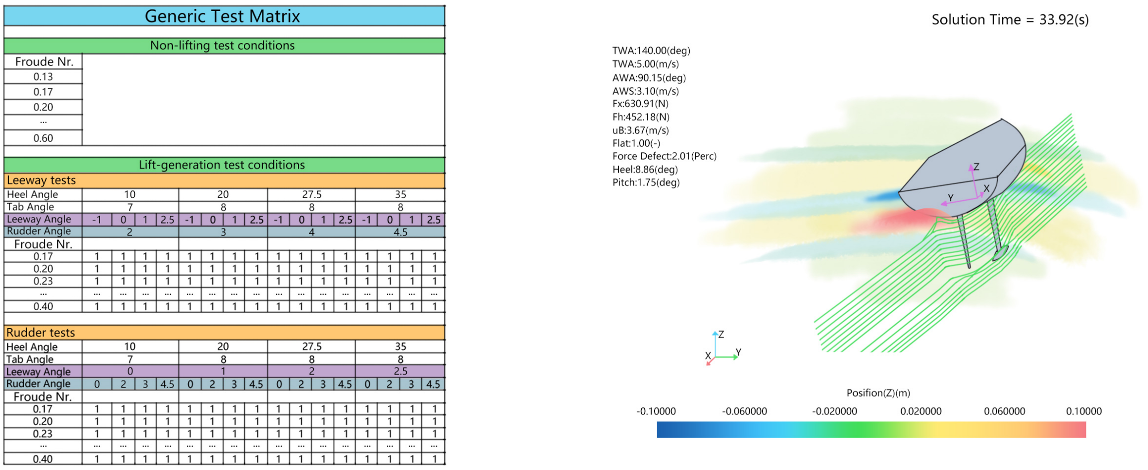
3.1. Central issues

Component-level evaluation focuses on understanding how individual aerodynamic and hydrodynamic elements, such as sails, foils, and appendages, contribute to the vessel's performance and dynamics. This task is uniquely challenging for sailboats due to their exposure to a wide range of environmental conditions and the inherent physical complexity of key components. In contrast to motor vessels, where component performance can often be evaluated under standard regimes, sailing components must be assessed under dynamic, unsteady, and highly varied operational contexts.

1. **Wide-range performance assessment:**

   Sailing components must operate across a continuous spectrum of apparent wind angles and speeds, unlike engines defined by fixed load curves. This sensitivity necessitates a substantially larger, resource-intensive test matrix to establish performance baselines, as illustrated in Figure 2a. Despite emerging guidelines from the International Towing Tank Conference (ITTC), characterizing this variability remains a primary engineering hurdle.

2. **Multiphysics modeling complexity:**



Generic Test Matrix																
Non-lifting test conditions																
Froude Nr.																
0.13																
0.17																
0.20																
...																
0.60																
Lift-generation test conditions																
Leeway tests																
Heel Angle	10				20				27.5				35			
Tab Angle	7				8				8				8			
Leeway Angle	-1	0	1	2.5	-1	0	1	2.5	-1	0	1	2.5	-1	0	1	2.5
Rudder Angle	2				3				4				4.5			
Froude Nr.																
0.17	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
0.20	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
0.23	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
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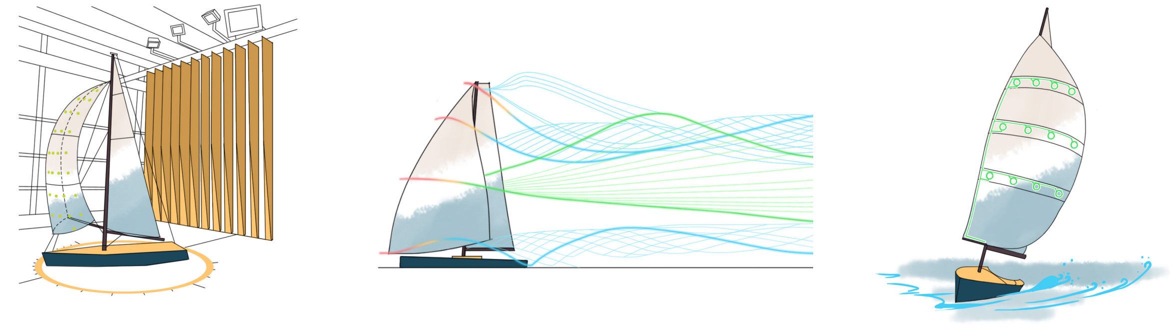
0.40	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Rudder tests																
Heel Angle	10				20				27.5				35			
Tab Angle	7				8				8				8			
Leeway Angle	0				1				2				2.5			
Rudder Angle	0	2	3	4.5	0	2	3	4.5	0	2	3	4.5	0	2	3	4.5
Froude Nr.																
0.17	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
0.20	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
0.23	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
0.40	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1

(a) Towing tank test matrix for hydrodynamic assessment, covering a wide range of operating conditions, adapted from [83]

(b) CFD simulation of wave patterns under a specific test configuration, adapted from [83]

Figure 2: Component-level hydrodynamic evaluation in sailing.



(a) Wind tunnel testing of soft sails under controlled conditions, adapted from [90].

(b) 3D CFD simulation of a soft sail, adapted from [91].

(c) On-water measurements using sail-mounted pressure sensors, adapted from [92].

Figure 3: Representative component evaluation methodologies.

Many components experience strong fluid—structure interactions and transient wave-induced loads. This ranges from soft sails fluttering under changing trim and hydrofoils deforming under dynamic lift, to canting keels subject to inertial coupling. Capturing these phenomena necessitates high-fidelity models that resolve unsteady aerodynamics, hydrodynamics, and structural responses, posing significant challenges for both simulation and experimental validation, as illustrated in Figure 2b.

These characteristics highlight the need for integrated aerodynamic and hydrodynamic analysis in both racing and autonomous sailboat design. Across both domains, understanding the coupled response of components under realistic conditions remains a fundamental task in performance modeling and system optimization [84, 85].

3.2. Methodologies

Evaluation methods for the aerodynamic and hydrodynamic performance of sailboat components are categorized into three primary approaches (Figure 3): laboratory testing, CFD simulation, and on-water measurements. Given the scope of this review, we provide a concise overview of these methodologies; for extensive discussion and technical details, readers are referred to [86, 87, 88, 89].

3.2.1. Laboratory testing

Laboratory testing remains a critical benchmark for validation, having served as the primary high-precision approach prior to the widespread adoption of CFD. These controlled assessments encompass both aerodynamic and hydrodynamic performance.

Aerodynamic evaluation primarily utilizes wind tunnels (Figure 3a) and water tunnels. Wind tunnels characterize sail shapes and airflow via cameras and smoke tracers [93, 94, 95, 96, 97]. However, the implementation of particle image velocimetry (PIV) remains technically challenging in air [98]. Conversely, water tunnels leverage higher fluid density to facilitate PIV for tracking seeded particles and capturing high-resolution flow dynamics [99, 100, 101, 102].

For hydrodynamic performance, towing tank tests are the standard benchmark for evaluating canoe body and appendage configurations across specific test matrices [103, 89]. However, the utility of these controlled experiments is fundamentally limited by the precision with which they address scale effects, as the nonlinear transition from laboratory Reynolds numbers to full-scale racing or large-scale robotic operations remains a primary source of uncertainty in performance projection.

3.2.2. CFD simulation

Aerodynamic CFD methods are categorized by increasing fidelity into potential flow, Reynolds-Averaged Navier-Stokes (RANS), and Large Eddy Simulation (LES). Potential flow assumes inviscid, incompressible, and irrotational fluid, making it suitable for simplified flows despite lacking turbulence and viscosity modeling [104, 105, 106]. The RANS method (Figure 3b) averages the Navier-Stokes equations and incorporates turbulence models, effectively balancing accuracy and computational efficiency for most engineering applications [104, 107, 108]. Conversely, LES resolves large-scale turbulence structures while modeling smaller scales, offering high transient accuracy but at a significant computational cost [109, 110, 111, 112].

For hydrodynamic performance, CFD offers several advantages over physical towing tanks, including the ability to simulate complex wave interactions, facilitate rapid shape iterations without physical prototypes, and perform full-scale simulations that better reflect real flow conditions [113]. The WIDE-LIGHT Project [28] exemplified this by comparing large-scale simulations with tank results for high-performance hulls, demonstrating that mainstream potential flow and RANS-based codes deliver reliable component evaluations more cost-effectively than physical testing. These findings substantiate a broader transition from reliance on physical experimentation toward simulation-driven optimization; however, the inherent sensitivity of turbulence models requires rigorous cross-validation against physical benchmarks to ensure the reliability of off-design predictions.

3.2.3. On-water measurements

On-water aerodynamic measurements (Figure 3c) typically employ dynamometer boats or instrumented platforms equipped with load cells and cameras to capture forces, moments, and "flying shapes" during operation [114, 115, 116]. This approach records component behavior in realistic environments that often differ significantly from laboratory settings, providing critical insights into real-world sail performance [117, 118, 119, 95]. Although dedicated instrumented vessels were developed in the late 1990s and early 2000s [120, 121, 122, 123], their usage declined as numerical simulations advanced. Despite the high uncertainty caused by environmental unsteadiness and the difficulty of quantifying wind and wave variations, field measurements retain significant value. For instance, while the leading-edge vortex on spinnakers has been evidenced numerically [108] and experimentally [100], it has yet to be fully captured in on-water conditions.

In contrast, on-water hydrodynamic measurements remain rare due to the challenges of installing high-precision sensors on underwater components without disrupting flow behavior, alongside high operational costs and complexity. Furthermore, the inherent randomness of ocean waves and currents often obscures localized hydrodynamic effects, making it difficult to isolate individual component performance from the overall system dynamics.

3.3. Contrasts and convergences

3.3.1. Racing sailing

To optimize aerodynamic performance, research focuses on characterizing forces, pressures, and flow structures [88, 124, 125]. Analysis generally distinguishes between upwind conditions, where sails function as lifting surfaces with minimal separation [126, 127], making them amenable to potential flow modeling [104], RANS simulations [111], and standard wind tunnel testing [97]. In contrast, downwind configurations (e.g., spinnakers) are characterized by high camber and massive flow separation [128, 129], necessitating high-fidelity techniques such as non-intrusive flow diagnostics [130], water tunnel tests [131], or Large Eddy Simulation (LES) coupled with Fluid–Structure Interaction (FSI) [112]. Notably, however, existing studies often focus on discrete "optimal" trim states derived from expert heuristics, rather than characterizing the entire parametric space of arbitrary sail shapes [15, 130].

Validation efforts, while critical, face significant hurdles. Although on-water measurements play a vital role [122, 92], they remain scarce compared to numerical and model-scale studies. As highlighted by [129], this leads to a persistent gap in cross-correlation with high-precision full-scale data; furthermore, complex dynamic aeroelastic phenomena, such as luff flapping, remain significantly under-explored. For a comprehensive methodological comparison, see [132].

In hydrodynamics, research prioritizes: (1) canoe body drag matrices accounting for yaw and roll [133]; (2) keel performance, including canting mechanisms [134, 135]; and (3) hydrofoils, utilizing lift for stability and speed [136, 137]. Recent work has also challenged infinite-depth assumptions by focusing on free-surface proximity effects [136]. However, analyzing components in isolation may neglect complex viscous interference drag at junctions, particularly hull–appendage interfaces, necessitating future research to quantify these effects for accurate resistance estimation.

Canoe body performance is evaluated via empirical formulas [18], towing tanks [138, 139], or CFD [140]; notably, the Delft Systematic Yacht Hull Series (DSYHS) [138] remains the benchmark, derived from over 50 hull and 13 keel configurations. Appendage analysis ranges from potential flow for simple fins [141] to RANS for bulbous/canting keels [142, 143]. Hydrofoils, subject to deformation and cavitation, require FEM coupled with RANS/FSI [144, 145, 146]. Despite this diverse toolkit, a universal resistance framework for arbitrary hull forms remains elusive. Empirical methods are constrained to their original parent families; hence, accurate performance prediction for novel geometries remains dependent upon computationally intensive, case-specific simulations.

3.3.2. Robotic sailing

In robotic sailing, aerodynamic performance evaluations focus on providing guidance for sail control and route planning rather than achieving highly accurate metrics [147]. Metrics often focus on lift and drag coefficients, presented as curves relative to the angle of attack, with less emphasis on the flow field [148, 149]. Autonomous sailboats, operating in mission-specific areas, emphasize general performance across various wind directions under specified wind conditions. Some studies evaluate various sail types to guide design choices regarding the most efficient propulsion system [150], while others investigate differences in energy consumption between types of sail due to the energy sensitivity of these vessels [151, 152].

Aerodynamic performance estimation in this branch tends to prioritize practicality over precision. While some studies employ Reynolds-Averaged Navier-Stokes CFD simulations [148, 153], many rely on potential flow methods [149] or pre-existing airfoil data [154] to approximate lift and drag coefficient curves as functions of the angle of attack for sail modeling. However, relying on such data may compromise accuracy for low-aspect-ratio sails by overlooking induced drag and tip vortices.

Compared to the racing branches, research on hydrodynamic component performance in robotic sailing is relatively limited. Many autonomous sailboats utilize scaled-down versions of existing designs, with adjustments often based on real-world performance rather than detailed analysis and evaluation [155]. Even in custom designs, optimization of hydrodynamic components is rarely reported [156, 157]. This underscores a prevalence of empirical trial-and-error design rationales over systematic performance optimization processes.

Most hydrodynamic performance estimates for canoe bodies in robotic sailing rely on established models, such as DSYHS. However, as noted in [158], unconventional canoe body designs in autonomous sailboats may fall outside the parameter ranges of these models, leading to potentially significant estimation errors. Only a few studies use Reynolds-Averaged Navier-Stokes CFD simulations to analyze hydrodynamic components, highlighting the need for more detailed evaluations [158].

3.4. Synthesis and transferability analysis

At the level of *component performance*, both domains pursue the same fundamental goal: to capture aero- and hydrodynamic characteristics of sails, hulls, and appendages so as to support higher-level modeling, control, and

Table 2: Transferability analysis of methods at the component-performance level

Aspect	Empirical relations	Laboratory testing	CFD simulation	On-water measurements
Potential for transfer	Low	High	High	Medium
Maturity leader	Racing	Racing	Racing	Racing
Main beneficiary	Robotic	Robotic	Both	Both
Current level of transfer	High	Medium	Medium	Low
Main obstacles	Out-of-range validity	Budget constraints	Computational cost	Miniaturization

routing. Racing domain typically relies on fine-grained evaluation tailored to specific, repeatable race conditions, whereas the robotic sailing community often adopts coarser, guidance-oriented assessments to prioritize robustness and simplicity. This asymmetry suggests that many racing-grade techniques can be downscaled and transferred to autonomous sailboats, provided their resolution and scope are adapted to mission needs (Table 2).

Regarding specific methods, the transferability of empirical and semi-empirical relations remains limited, despite their widespread adoption for direct application. Aerodynamic polars (e.g., NACA 2D) and hydrodynamic relations (e.g., DSYHS) largely originate from idealized two-dimensional or laboratory settings; their validity is bounded by operating conditions and nondimensional parameters. When extrapolated to finite-aspect-ratio, three-dimensional lifting surfaces and to smaller craft operating at lower Reynolds numbers (Re), significant bias can arise unless 3D induced-effect corrections and low-Re adjustments are applied.

Beyond specific empirical data, laboratory testing itself remains highly transferable and potentially more faithful for autonomous platforms. Unlike racing contexts where a 2-meter model typically represents a 20-meter yacht, introducing significant Reynolds number discrepancies, autonomous sailboats often operate at or near this model scale (e.g., 2 meters). This proximity to full-scale conditions inherently minimizes scale effects, allowing laboratory results to directly predict real-world performance without complex scaling corrections. Likewise, CFD workflows developed for racing sailboats can be transferred with modest adaptation. Because many autonomous platforms use rigid wingsails instead of soft sails and face simpler operating conditions, applying the same workflows in simplified form is usually sufficient. The primary barrier to broader adoption for both laboratory testing and CFD workflows is resources rather than methodology: racing projects, structured by class rules, generate reusable datasets and benefit from substantial commercial and institutional support, including routine access to wind tunnels, towing tanks, and high-performance computing. In contrast, autonomous platforms are commonly mission-specific and often ad hoc in design; since their data and hardware are less reusable across campaigns and economies of scale are harder to realize, they tend to operate under tighter budgets.

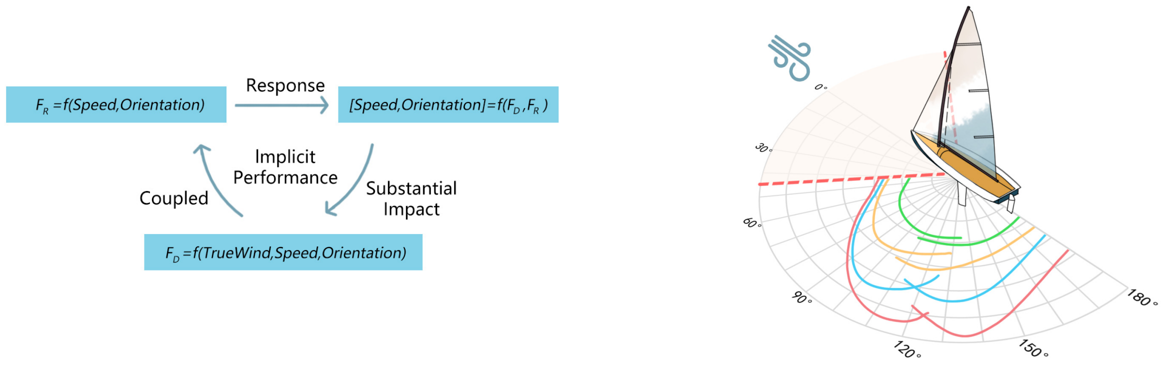
On-water, component-level aero- and hydrodynamic measurements have seen little adoption in autonomous sailboats to date. Feasibility is currently constrained by the size and power requirements of sensors and actuators as well as the footprint of mechanical transmission hardware. Integration complexity compounds these constraints, and miniaturization remains the principal bottleneck. As the robotic sailing community places greater emphasis on platform performance and as compact, low-power instruments mature, uptake should improve. In addition, the lower retrofit cost and risk profile of autonomous platforms make them attractive as early-stage testbeds for innovative rigs and appendages, providing a rapid-iteration pathway that can ultimately feed back into the racing community.

4. Overall Performance Evaluation

4.1. Central issues

Overall performance modeling addresses the integrated behavior of the entire sailboat system under coupled aerodynamic and hydrodynamic forces. As shown in Figure 4, unlike motor vessels, where propulsion is nearly decoupled from heading and environmental states, sailboats exhibit complex feedback loops involving sail trim, heading, apparent wind, and hull behavior. This makes accurate system-level modeling indispensable for control, design, and mission planning.

1. **System-level nonlinear coupling:**



(a) Nonlinear system-level coupling between propulsion, drag, and orientation leads to implicit performance behavior that cannot be predicted analytically.

(b) Resulting directional dependency under varying wind speeds and headings necessitates full-range performance evaluation, adapted from [80].

Figure 4: Overall performance evaluation challenges in sailing.

Performance emerges from a nonlinear interaction among sails, hull, rudder, and environment. For example, a change in sail trim alters the boat's heading, which in turn modifies the apparent wind, ultimately feeding back into sail performance. These feedback loops require integrated modeling frameworks that capture dynamic coupling across domains, from aerodynamics to kinematics to sea state.

2. **Directional dependency evaluation:**

   Sailboats exhibit strong direction-dependent performance, with efficiency varying sharply by apparent wind angle. Maneuvers like tacking are required for upwind motion, and sail trim differs across points of sail. A key metric is velocity made good (VMG), the component of speed toward a target direction, often upwind. Since no single curve captures all conditions, full performance maps are essential for maneuvering and path planning.

Performance evaluation in sailing is commonly divided into two forms: instantaneous and cumulative. Instantaneous performance characterizes the vessel's optimal behavior at a given moment, typically expressed as a function of true wind angle and speed. It reflects the anisotropic velocity profile achievable under different environmental conditions. This form of evaluation is fundamental in both racing and robotic sailing: it provides a quantitative benchmark for design comparison, supports real-time control strategies, and guides path planning algorithms.

Cumulative performance, in contrast, measures the integrated outcome over a period of time or along a route. In racing sailing, it is typically expressed as the total time to complete a course under given weather conditions. However, cumulative performance evaluation is rarely emphasized in robotic sailing, where missions are usually nonstandardized and locally adaptive. In such cases, robustness and moment-to-moment responsiveness often take precedence over long-term optimization.

4.2. Methodologies

Across the branches, three interrelated frameworks are used for performance evaluation: the velocity prediction program (VPP), dynamic velocity prediction program (DVPP), and race modeling program (RMP). Their structures and comparisons are illustrated in Figure 5.

4.2.1. Velocity prediction program

The VPP is the foundational tool and the most widely used in the sailing field to assess the overall instantaneous performance of a sailboat amidst the complexities of coupled dynamics. VPP was first introduced by Kerwin in

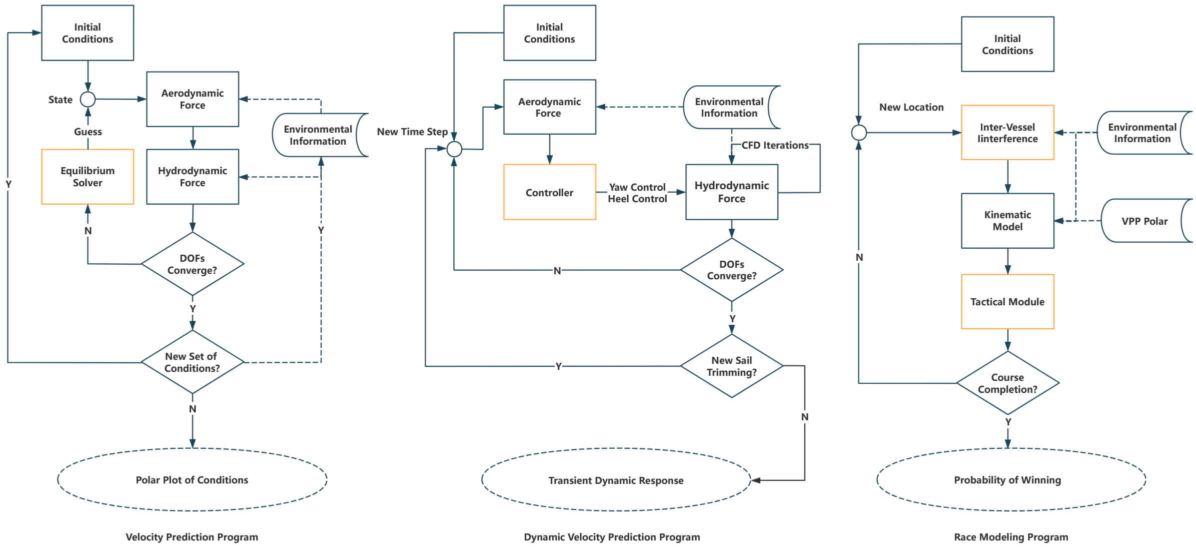


Figure 5: Flowchart of the three performance evaluation frameworks

the 1970s [70]. Its basic framework involves entering specific environmental conditions of interest, such as true wind speed and angle, and then using hydrodynamic and aerodynamic models to calculate the forces acting on the components. The program then solves for the steady-state condition that maximizes boat speed while maintaining balance across a selected number of degrees of freedom. This steady state is ultimately considered the performance of the boat under particular wind conditions [159]. The results are typically represented in a polar diagram (Figure 4b), where different lines indicate different true wind speeds, and each point on a curve represents the speed of the boat at a specific wind angle. In recent years, there has been an increased focus on VPP for hydrofoiling boats [79, 160, 161] and wind-assisted ships [162, 163, 164].

4.2.2. Dynamic velocity prediction program

The DVPP, initially developed by Day [165, 166], was designed to address the limitations of traditional VPPs in the study of high-speed racing sailboats, especially those equipped with hydrofoils that transition between displacement and hydrofoiling modes. Although VPPs provide optimal steady-state performance, they cannot describe how a sailboat reaches that state or what happens during transient phases. The basic structure of the DVPP is illustrated in Figure 5 [159, 26].

DVPP typically begins with an initial state, often derived from a static VPP or estimated iteratively [167, 168]. Control is applied using a preset control rule, commonly a simple PID controller, in accordance with competition regulations [166, 169]. The forces on each component are calculated using CFD simulations, which determine the acceleration. The state at the next time step is then computed by integrating the current step's acceleration. This iterative process continues until equilibrium is reached in all selected degrees of freedom, offering optimal sail adjustments and a detailed prediction of the dynamic response of the boat. The DVPP outputs either an instantaneous performance evaluation with detailed process information or a short-term cumulative performance evaluation, providing insights into the transient behaviors of high-speed racing sailboats.

4.2.3. Race modeling program

RMPs are specialized software systems developed to evaluate cumulative performance in specific racing sailing venues and analyze winning probabilities by incorporating various race strategies. The primary objective is to determine the time differences between two boats completing a course under varying wind conditions. Initially introduced in 1987, early RMP versions simply combined predicted VPP performance data with wind distributions to estimate win probabilities [170]. Over time, RMPs have advanced to include tactical modules and boat-to-boat interference models, significantly enhancing their analytical capabilities.

The basic framework of an RMP operates as follows: Starting from initial conditions (including environmental factors and boat position), a kinematic model of the specific sailboat is established, often derived from VPP predictions. The tactical module then guides maneuvers based on wind and wave conditions, as well as optional right-of-way rules, adjusting the sailboat's heading to reach successive positions [171, 172]. Meanwhile, the interference model evaluates the interactions between boats [173]. This iterative process continues until the entire race course is completed, providing a detailed assessment of performance and competitive dynamics.

4.3. Contrasts and convergences

4.3.1. Racing sailing

For sail aerodynamics, the system evaluation integrates force inputs derived from wind or water tunnel tests, and CFD simulations. These inputs incorporate adjustment coefficients such as *reef* and *flat*, *ease* and *twist*, or *depower* to account for trim changes [174, 175, 167, 176]. Although these input models may not precisely predict pressure distributions, they provide reliable net force estimates based on primary sail dimensions. Additionally, regarding fleet scenarios, boat-to-boat aerodynamic interference models, typically pre-calculated from CFD simulations of hundreds of close-distance scenarios, are called upon in RMPs to estimate cumulative performance degradation [107].

For hydrodynamic force acquisition, established databases are often queried, allowing for approximate performance estimates based on the principal dimensions of the canoe body and appendages [18]. Another prevalent approach involves interpolating from surrogate models built upon water tank experiments or CFD simulations. These surrogate models are constructed from predefined test matrices (typically 80–100 simulations) covering various speeds, heel angles, and yaw angles [177, 178, 83]. In DVPP applications, rather than relying on precomputed databases, CFD simulations are often executed on-demand during the prediction process to capture wave-induced transient responses [166].

Integrating these force inputs into global performance solvers, VPPs typically employ three to six degrees of freedom (DOFs). For Archimedean mode, surge, sway, and roll are the most critical, with heave and pitch often omitted in four-DOF models, whereas for hydrofoiling boats, six DOFs are generally preferred [179]. In Dynamic VPPs (DVPPs), six DOFs are commonly employed as the standard. Racing sailing benefits from extensive research on component performance evaluation and a wealth of competition data, enabling the use of high-fidelity models. However, current evaluation approaches face certain limitations. Traditional VPPs are fundamentally oriented towards steady-state equilibrium, leaving transient fluid-structure interactions, which are essential for dynamic maneuvering, outside their primary scope. While DVPPs address these dynamics, their high computational cost typically restricts them to short-duration events, creating a need for efficient methods that balance maneuvering fidelity with computational feasibility. Furthermore, regarding adversarial fleet racing where RMPs are typically used to predict win probabilities, although they account for physical inter-vessel aerodynamic interference, the strategic dimension of sailing has received comparatively less emphasis. To fully capture the complex tactical decision-making inherent in competitive racing, future evaluations would benefit from integrating game-theoretic approaches based on the Racing Rules of Sailing (RRS).

4.3.2. Robotic sailing

In robotic sailing, aerodynamic force acquisition typically relies on precomputed models, such as lift-to-drag curves parameterized by the angle of attack. These inputs are sourced from basic 2D CFD simulations or standard airfoil databases [180, 181, 182]. In some cases, 3D CFD simulations are utilized to generate force coefficients, but even then, the sail angle is usually treated as a fixed input parameter rather than a dynamically controlled variable [183].

For hydrodynamic forces, system evaluations often call upon empirical formulations, with the DSYHS serving as the most frequently utilized input source [184, 185]. However, the DSYHS implies a hull form based on conventional yachts, which may not be directly applicable to autonomous sailboats that often feature nonstandard shapes (e.g., spindle-like bodies) and significantly smaller scales [158]. While the DSYHS includes formulations for added resistance in waves, these terms are rarely activated in robotic sailing models, largely due to the lack of real-time wave sensing on small platforms. Consequently, wave effects are often neglected in the force summation. Considering the pronounced influence of waves on lightweight hulls, however, this omission may introduce significant prediction errors.

In the context of overall performance evaluation for robotic sailing, 3–6 degrees of freedom (DOFs) are typically considered, with 4 DOFs commonly adopted as a trade-off between model fidelity and computational efficiency. Among these, surge, sway, yaw, and roll are typically retained, while pitch and heave are often neglected. Force acquisition in this domain is generally based on simplified modeling approaches. This stems from two main challenges: first, the reuse of platform designs and limited evaluation resources, as previously discussed, has led to a modeling culture that favors qualitative trends over precise quantitative accuracy [186]. Second, the lack of operational data, such as class-specific performance records commonly available in competitive sailing, forces standard solvers to blindly explore a vast state space without prior constraints. This computational bottleneck highlights the critical necessity of developing methods capable of *rapidly identifying equilibrium states*, thereby minimizing the waste associated with sampling irrelevant, non-equilibrium conditions.

4.4. Synthesis and transferability analysis

At the level of *overall performance evaluation*, both domains share the same fundamental goal: to assess how a given design performs across different environmental conditions so as to improve the design and to support decision-making for human control in racing and for autonomous control in robotic sailing. Racing studies typically focus on well-specified race conditions and track both instantaneous responses and cumulative outcomes; they also extend beyond steady-state predictions by analyzing how equilibrium is reached. By contrast, robotic sailing studies usually cover a broader operating envelope yet rely primarily on instantaneous performance metrics. Because the racing literature is deeper and longer established, its objectives largely subsume those of autonomous sailing, which provides a sound basis for methodological transfer (Table 3).

Regarding specific methods, only VPPs are transferable. DVPPs resemble the dynamic models used in robotic control in form; however, they are typically run offline at higher computational cost to resolve performance over time-evolving scenarios rather than to provide a real-time, control-oriented state-space model. RMPs focus on relative performance among competing designs in a regatta context, which does not align with typical autonomous-sailing missions.

Although VPP techniques can be transferred, several obstacles must be recognized. First, overall performance modeling fundamentally depends on the availability and operating-envelope coverage of component-level force data. Racing platforms can exploit empirical and semi-empirical relations to estimate loads under specific conditions, whereas autonomous platforms often require new simulations or experiments, which raises cost. Second, a fundamental difference is the availability of performance priors: for a class-regulated design and a given condition, plausible performance ranges can often be estimated from class-defined configurations or abundant empirical data. As a result, component testing can target a narrow design envelope and typically requires on the order of 80—100 runs per platform [177, 178, 83]. Robotic sailboats face greater uncertainty in both design and environment, which greatly expands the test matrix and increases computational expense. Third, wave corrections for VPPs and their validation are more tractable in racing, which benefits from extensive competition data and rich onboard instrumentation that enable direct validation against race outcomes [187, 188]. In contrast, autonomous sailboats operate in unstructured environments with limited telemetry and scarce ground-truth data, which makes full-system validation considerably more difficult [184, 158].

The first two obstacles motivate the robotic sailing community to adopt reduced-DOF models that balance fidelity and computational cost, and to pair them with optimal sampling and simulation-driven design to accelerate the solution of VPPs under weak performance priors and to mitigate the curse of dimensionality in the test matrix [158, 37]. These aims align with simulation-driven design for new racing configurations [178, 189], enabling bidirectional knowledge transfer between the communities. The third obstacle is harder to address in the near term, both because waves exert a proportionally larger influence on smaller craft and because representative in situ sea states for autonomous platforms are difficult to obtain.

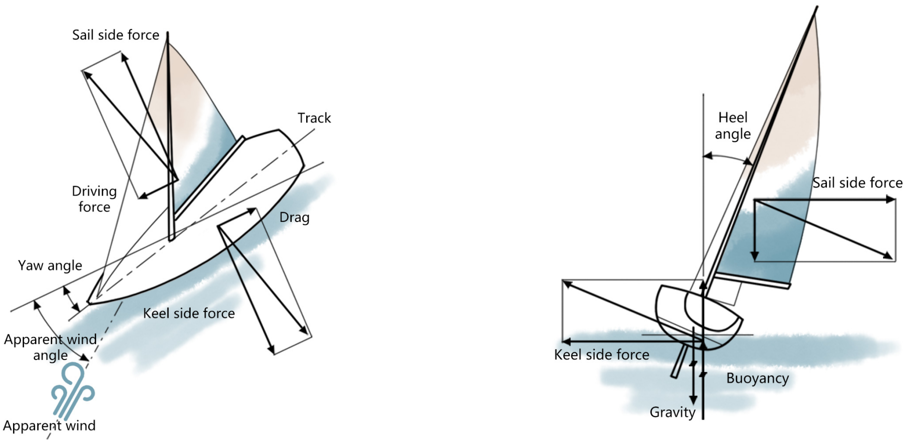
5. Motion Control

5.1. Central issues

Adapting Fossen's marine-craft framework [190], sailboat motion control can be defined as the regulation of the vessel's position, heading, and speed through sail, rudder, and appendage commands that shape the net aero-hydrodynamic forces and moments under wind and current. Motion control for sailboats differs fundamentally from

Table 3: Transferability analysis of methods at the overall-performance-evaluation level

Aspect	VPP	DVPP	RMP
Potential for transfer	High	Medium	Low
Maturity leader	Racing	Racing	Racing
Main beneficiary	Both	Robotic	-
Current level of transfer	Medium	Low	Low
Main obstacles	Costly data Sampling explosion	Sampling explosion Real-time requirement	Mismatched objectives



(a) Dynamic yaw disturbances induced by unsteady lateral aerodynamic forces from the sail.

(b) Coupled relationship between speed and heeling, where increased propulsion inherently generates destabilizing roll moments.

Figure 6: Motion control challenges in sailing, adapted from [141].

that of engine-driven vessels due to the uncontrollability and directionality of wind propulsion (Figure 6). Thrust cannot be commanded directly but must be shaped through sail configuration and heading adjustments. This leads to control objectives that must continuously balance propulsion, stability, and maneuverability, especially under changing environmental forces.

Additionally, because sails rely on environmental wind for propulsion, available thrust is neither guaranteed nor immediately responsive, complicating precise directional control compared to engine-powered systems.

1. **Dynamic yaw disturbances:**

   Unlike engine-driven vessels that generate thrust aligned with the hull, sails produce lateral forces whose direction and magnitude fluctuate with wind conditions and sail trim. These side loads interact with the hull and rudder, inducing yaw disturbances that require continuous rudder compensation. As a result, heading stability is highly sensitive to apparent wind angles and sea states [191, 192].

2. **Speed-–heeling trade-off:**

   While generating propulsion, sails also induce heeling moments. This inherent coupling means that, under constantly changing ocean conditions, pursuing higher speeds often requires careful management of heel to preserve both performance and safety. The trade-off becomes particularly critical in unsteady wind and wave environments [103, 193].

In racing sailing, control focuses on maximizing performance. The goal is to dynamically trim complex soft sails for optimal thrust and to steer for maximum VMG toward the race target. Precise tracking is less emphasized, while position-keeping is briefly required at race starts or during tactical maneuvers.

In robotic sailing, control emphasizes robustness under environmental disturbances. To ensure safe operation, speed control prioritizes maintaining sufficient propulsion while limiting excessive heeling, rather than pursuing maximum velocity. Heading control [61], path tracking [194, 195, 196], and position maintenance [197, 198] (e.g., virtual anchoring) are further emphasized due to specific task requirements.

5.2. Methodologies

Sailing control encompasses a range of strategies that reflect varying levels of human involvement, mechanical assistance, and algorithmic autonomy. This section reviews these three layers of control, highlighting their mechanisms, objectives, and use across different sailing domains.

5.2.1. Manual control

Manual control in sailing refers to direct human operation of sails, steering, and body position without intermediary automation. It is central to racing sailing, present in both ocean-going yachts and inshore dinghies. In all cases, manual control relies on the sailor's real-time perception, skill, and decision-making to respond effectively to changing environmental conditions.

- **Sail trim:**

  Sail trim directly controls propulsion by adjusting the sail's shape and its angle to the apparent wind. On ocean-going yachts, large sails are operated using mechanical systems such as winches, blocks, and cleats, often supported by high-tension sheet setups or electric winch assistance. Sheet tension and sail shape are controlled through devices like travelers, boom vangs, outhauls, and cunninghams, typically operated via winches or lever systems to handle higher loads. In contrast, inshore dinghies employ the same set of trimming controls, but rely entirely on manual input. While blocks and cleats are still used, sailors adjust sheet tension, vang pressure, outhaul, and cunningham directly by hand, without powered assistance. This demands rapid reflexes and constant attention, as small dinghies respond sharply to wind shifts and lack mechanical advantage.

- **Helm:**

  Helming governs the boat's heading and is executed via a wheel or tiller. Ocean-going yachts often use wheels connected to the rudder by mechanical or hydraulic linkages, offering greater leverage but lower responsiveness. Passive control or autopilots may be used during long passages, with manual input reserved for tactical or fine maneuvers. In dinghies, steering is performed through a tiller directly connected to the rudder, providing immediate feedback. Sailors often steer one-handed while simultaneously trimming sails with the other, making balance and dexterity crucial. Minor tiller adjustments are tightly coupled with trim and body position to prevent loss of control, especially in gusty conditions.

- **Righting moment management:**

  Ocean-going racing yachts manage righting moment primarily through ballast-based strategies [199], including canting keel, water ballast systems, and tactical relocation of equipment or sails, commonly known as stacking. While crew may still shift their weight windward by sitting on the rail, their contribution is relatively limited due to the vessel's large mass and low crew-to-weight ratio. In contrast, inshore dinghies lack onboard ballast and rely almost entirely on crew-weight-based strategies. Sailors use hiking straps, trapezes, or wings to dynamically reposition their body weight, continuously resisting heeling forces in response to wind variations. Effective hiking not only preserves stability but also enables more aggressive sail trim by increasing the tolerable sail force before the risk of capsize becomes critical. In addition, surface-piercing hydrofoils are sometimes employed to augment dynamic stability; as the boat heels, increased foil immersion generates greater righting moment.

5.2.2. Passive mechanical control

Passive mechanical control refers to mechanisms that regulate sailboat behavior through intrinsic physical feedback, without relying on sensors, actuators, or computational input. These systems achieve stable and adaptive responses through mechanical linkages or geometry-driven feedback, offering robustness with minimal complexity.

They are widely adopted in both racing and autonomous sailing. In the racing domain, passive mechanisms help reduce crew workload during long-distance races and repetitive maneuvers [167, 169]. In autonomous sailing, they serve a different purpose, minimizing energy consumption while ensuring functional reliability during long-term, power-constrained missions. Notable examples include self-steering systems, surface-piercing hydrofoils, the Magic Wand mechanism, and self-trimming wings, as illustrated in Figure 7.

- **Self-steering systems:**

  Self-steering systems [200] have been used since the early 20th century and are particularly popular in solo or short-handed offshore racing. These systems typically consist of a wind vane mechanically linked to a flap, which itself is linked to the rear of the rudder (as shown in Figure 7a). When the wind direction shifts relative to the boat, the vane rotates and triggers rudder movement to maintain a constant apparent wind angle. This closed-loop behavior [201, 202], implemented entirely through mechanical linkages, enables stable heading control over long periods without power consumption or electronic supervision.

- **Surface-piercing hydrofoils:**

  Surface-piercing hydrofoils [203] (Figure 7b) offer passive roll stabilization by exploiting geometric nonlinearity. Their V-shaped profiles generate lift that increases with immersion depth. As the vessel heels, the leeward foil immerses deeper and produces more lift, naturally restoring upright posture. This form of self-regulating behavior requires no sensors or actuators and is especially useful in classes like the IMOCA or early-generation multihulls, where full active foil control is prohibited or impractical.

- **The Magic Wand system:**

  The Magic Wand system [204] (Figure 7c) is a semi-passive altitude control mechanism widely used in high-performance foiling classes such as the International Moth. It consists of a wand, a lightweight, spring-loaded rod, that extends forward from the bow and maintains contact with the water surface. Changes in flight height modify the wand angle, which actuates a push-rod mechanism connected to a flap on the main T-foil. This mechanical feedback adjusts the foil's lift in real-time, stabilizing the ride height without the need for sensors or computation. Despite its simplicity, the system enables stable and efficient hydrofoil flight at high speeds [167].

- **Self-trimming wings:**

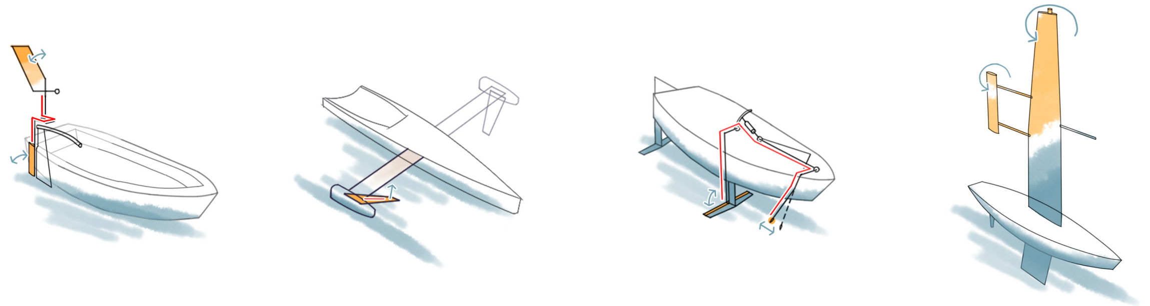
  Self-trimming wings [149, 40] (Figure 7d) are often used in rigid wingsail configurations, particularly in autonomous platforms. These systems mechanically couple the main wing to a smaller aft tail or trim tab, which acts like the horizontal stabilizer of an aircraft. Changes in relative wind direction cause the tail to deflect, adjusting the angle of the main wing accordingly. This aerodynamic feedback loop allows the wing to maintain an optimal angle of attack without active control, reducing the need for sensors, actuators, or real-time computation.

5.2.3. Autonomous control

Autonomous control in sailing refers to the use of sensor-based feedback and decision-making algorithms to regulate sail and rudder settings without continuous human intervention. It is employed in both autonomous sailboats and ocean-going yachts. In both cases, the primary goal is to maintain stability, efficiency, and safety under uncertain and dynamic environmental conditions, with the capability to execute complex maneuvers in response to mission objectives. Methods are generally divided into model-free and model-based approaches, each offering distinct trade-offs in implementation complexity, adaptability, and robustness.

- **Model-free methods:**

  Model-free methods treat the sailboat as a black box, using direct feedback from the environment to guide control actions without relying on explicit dynamic models. Classical implementations include PID controllers, which adjust rudder or sail trim based on error feedback loops [205], and fuzzy logic controllers, which encode



(a) Self-steering system, which uses a wind vane linked to the rudder to passively maintain heading.

(b) Surface-piercing hydrofoils, which provide roll stability through immersion-dependent lift.

(c) Magic Wand system, which adjusts foil flaps via a water-tracking wand to regulate flight height.

(d) Self-trimming wings, which passively align to the wind via aerodynamic feedback between wing and tail.

Figure 7: Mechanical control systems in sailboats.

human-like decision rules derived from sailing experience or VPP outputs [206]. These techniques are computationally efficient and simple to tune, but their performance can degrade in highly dynamic or uncertain ocean conditions [207, 208].

Recent advances in reinforcement learning (RL) have introduced adaptive control strategies that optimize behavior through trial-and-error interactions with the environment [209, 210]. When combined with neural networks, RL enables control in complex, nonlinear systems [211, 212], but requires extensive data or high-fidelity simulators. The resulting models often suffer from poor generalization, especially when transitioning from simulation to real-world conditions.

- **Model-based methods:**

  Model-based methods employ dynamic representations of sailboat behavior under wind and hydrodynamic forces. While full 6-DOF models offer high fidelity [190, 213], most control applications rely on 4-DOF formulations that neglect heave, pitch, and certain external disturbances for tractability [214, 215, 216]. Regardless of the degree of freedom, these dynamic models typically decompose sailboat motion into the contributions of key components, sail, canoe body, rudder, and keel, whose combined forces determine the overall motion response.

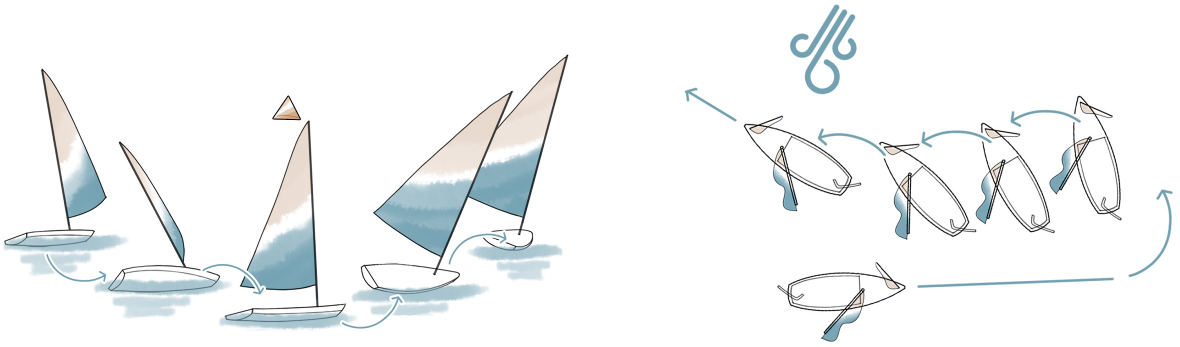
  Within this category, Lyapunov-based methods aim to guarantee stability through structured control laws. Examples include backstepping [217], sliding mode control [218], and feedback linearization [219]. Alternatively, optimization-based controllers, such as model predictive control (MPC) or linear quadratic regulators (LQR), formulate control as a constrained optimization problem to minimize trajectory error or energy use [220, 221, 222]. These methods offer flexibility but demand greater computational resources, posing challenges for real-time deployment.

  Model-based control holds theoretical promise but is constrained by significant modeling challenges. VPPs and DVPPs are often mistaken for control models, but in fact serve to estimate steady-state performance under expert-optimized trim conditions [15, 130]. Their outputs, such as discrete reef levels or optimal sail shapes, are not directly applicable in autonomous settings, where many platforms employ rigid wingsails without trim actuators. As a result, conventional soft-sail control parameters such as *reef*, *ease*, *twist*, and *depower* become inapplicable [18, 167, 168].

5.3. Contrasts and convergences

5.3.1. Racing sailing

In inshore dinghies, manual control is the primary and often the only permitted mode of operation, with class rules generally prohibiting automated actuation. Aside from a few cases that allow limited passive mechanical aids, such as the “Magic Wand” system in the International Moth for altitude regulation, as previously discussed, sailors must



(a) Roll-tacking uses induced heel to assist turning, adapted from [224].

(b) Heaving-to stabilizes the boat with opposing sail and rudder forces, adapted from [225].

Figure 8: Advanced coordinated control techniques in sailing.

actively manage all control variables. These include sail trim, rudder angle, body position, and the deployment depth of daggerboards or hydrofoils.

This form of control is fundamentally model-free, relying on real-time sensory feedback, intuitive heuristics, and experience-based judgment rather than formalized mathematical models. Nevertheless, sailors achieve high levels of performance despite the absence of precise models for deformable sails and complex fluid–structure interactions [130, 223]. Through continuous coordination of sail trim, steering, and body movement, they maintain dynamic balance and optimize speed under rapidly changing wind and wave conditions. Such coordination enables advanced maneuvers, including roll-tacking, using deliberate heel to accelerate after a turn in light air, and heaving-to, which slows the vessel in strong winds by backing the sail while applying opposing rudder (Figure 8). The effectiveness of these manual techniques continues to motivate research into the principles of expert-level sailing control [224, 179].

In offshore racing, World Sailing's RRS 52 ("Manual Power" [226]) mandates that adjustments to sails, rigging, spars, and movable hull appendages be crew-powered. In solo IMOCA events (e.g., the Vendée Globe), class rules allow only narrow exceptions, for powered canting-keel operation, autopilot yaw control, and ballast transfer, while sail trim and other rigging adjustments remain human-powered and other servo-control is prohibited [227]. In this setting, modern autopilots reportedly steer about 95% of helm time in the Vendée Globe [228]. Outside competition, the cruising market offers commercial "automatic sail trim" systems, notably Assisted Sail Trim (AST), which integrates sensors with reversible electric winches to deliver auto tacking, auto trim, and a heel-limit function that automatically eases the mainsail to cap heel; the system targets shorthanded cruising in moderate conditions (typically 5—25 kn [229, 230]). To date, except for advantages in actuation frequency, consistency, and sustained attention over long durations, there is no published evidence that such automation consistently outperforms expert sailors.

5.3.2. Robotic sailing

Unlike racing sailboats, robotic sailboats operate without human control, relying entirely on a combination of passive mechanical structures and autonomous control algorithms. To extend endurance and reduce energy demands, passive mechanisms such as wind-vane self-steering and self-trimming wings are widely employed [231, 148]. These mechanisms exploit aerodynamic and hydrodynamic feedback to maintain stability or heading without sensors or active actuation.

At the algorithmic level, robotic sailboat control is typically divided into two tasks: speed and heel regulation, and heading control. The former is handled through sail or wing deflection to manage thrust and lateral forces [148], while the latter is governed by rudder input. Most systems adopt a decoupled structure, wherein these two tasks are addressed independently [232].

Speed and heeling control has traditionally relied on model-free methods, including rule-based tables or empirical functions derived from field testing or VPP outputs [233, 153, 234]. While straightforward to implement, such methods often perform poorly under variable environmental conditions. To improve adaptability, some works have introduced performance-aware controllers that dynamically optimize sail settings based on real-time feedback or simplified physical models [208, 235]. Due to limited roll control capabilities, early robotic sailboats often adopted conservative designs, such as oversized keels or undersized sail areas, to passively reduce heeling and avoid the need for explicit roll regulation [158, 82, 236]. More recently, a paradigm shift has occurred towards model-based control strategies that explicitly incorporate heeling constraints [196, 237, 238, 239]. This transition introduces a critical new perspective: by enabling efficient, aggressive performance tuning, departing from the reliance on overly conservative design, it is poised to unlock substantial improvements in the platform's overall performance.

Heading control has evolved from classical PID and fuzzy logic methods [240, 241] to more advanced model-based strategies. These include feedback linearization [219], backstepping control [216], sliding mode control [242], and model predictive control [221], which offer improved robustness and accuracy. Xiao's 4-DOF model remains a popular foundation for such controllers due to its balance between complexity and real-time feasibility [216].

While most systems still treat sail and rudder control as independent loops, their physical interaction is inherently coupled, each influencing the vessel's dynamics in nontrivial ways [243]. Emerging research is beginning to explore integrated control frameworks that jointly optimize these actuators for enhanced performance [244, 245]. This direction is particularly critical: since sailboats are inherently strongly coupled systems, treating actuators independently introduces errors of a magnitude far greater than in loosely coupled systems. Therefore, joint optimization represents a fundamental step toward achieving advanced autonomous control and adaptability in robotic sailing.

5.4. Synthesis and transferability analysis

At the level of *motion control*, competitive racing programs prioritize maximizing speed while keeping heel within acceptable bounds, whereas much of the robotic-sailing literature emphasizes heading and path-following accuracy, with heel often managed passively through generous static stability rather than by active roll regulation. This contrast does not imply that speed or attitude are unimportant in robotic sailing. For long-range missions, overweight hulls and low cruising speeds extend absolute mission duration, and recent studies have begun to emphasize speed optimization via control [245, 237]. Thus, despite the limited cross-fertilization to date between the two fields, there remains substantial scope for methodological transfer (Table 4).

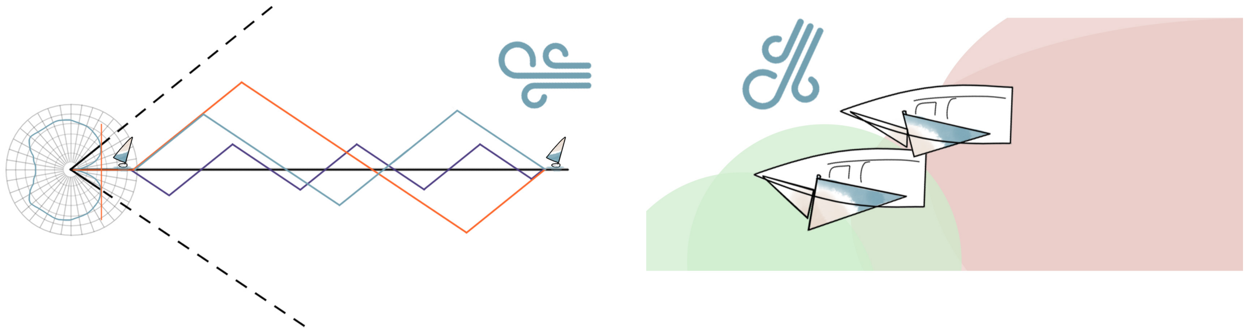
On the passive-mechanical side, the robotic community has already benefited from the racing domain's accumulated know-how. Self-steering systems and self-trimming wings are widely deployed on autonomous sailboats; originally intended to reduce crew workload, they now reduce onboard energy consumption and extend endurance. Passive hydrofoils and the so-called Magic Wand system have not yet seen widespread use on autonomous platforms, yet they offer substantial potential to increase speed and enhance stability with essentially no energy cost.

On the autonomous-control side, bespoke platform designs and stringent real-time requirements constrain the direct reuse of component-level performance datasets and DVPP frameworks, as noted above. Stronger wave-induced disturbances on smaller craft further complicate accurate dynamical modeling and diminish the practical advantages of purely model-based controllers across many operating regimes. To our knowledge, there is no conclusive evidence that current state-of-the-art controllers consistently outperform a trained novice sailor, who can often balance speed and heel gracefully (at relatively low control frequencies). A promising alternative is to capture expert sailors' actions and strategies as behavioral data and transfer them via imitation learning or reinforcement learning; behavioral studies from the racing community may be particularly valuable in this context [246, 247]. For the racing community, advances in autonomous control can operate as continuous testbeds for simulation-driven design and at-sea prototyping, as explored in [248]. Finally, in areas constrained by racing rules, such as sail trimming, there is scope for more open development within the robotic domain, which may indirectly broaden autopilot capabilities for both racing and leisure craft.

In terms of manual control, racing sailing inherently emphasizes the athlete's skill, which fosters a natural resistance to automation. This, however, does not imply that technologies developed for autonomous sailboats cannot benefit the racing community. On the one hand, semi-autonomous training boats could substantially lower the barrier of entry for novices and sailors with disabilities while improving the safety of training activities. In robotic sailing, sail and rudder control loops are typically decoupled, enabling a gradual division of control: beginners may manually operate one loop, such as steering,while the system automatically manages the other, such as sail trim or balance. This staged approach simplifies the human-–machine interaction and makes learning to sail more accessible. On the other hand, even for elite sailors, a highly capable intelligent robotic training partner or virtual opponent can create

Table 4: Transferability analysis of methods at the motion-control level

Aspect	Passive mechanical control	Autonomous control	Manual control
Potential for transfer	High	High	High
Maturity leader	Racing	Robotic	Racing
Main beneficiary	Robotic	Both	Robotic
Current level of transfer	High	Low	Low
Main obstacles	-	Rule constraints Limited attention	Data requirement Limited attention


(a) Required zigzag maneuvers in wind dead zones, with multiple viable paths, adapted from [211].

(b) Wind shadow effects from nearby vessels: red zones hinder others and benefit the casting boat; green zones offer potential gain to competitors, adapted from [251].

Figure 9: Path planning challenges in sailing.

a mutually beneficial learning environment, where practice against a responsive, high-level agent sharpens tactical and technical skills. A readily understood analogy is the impact of AlphaGo on the game of Go [249]; its significance was not merely defeating top human players but providing every player with an on-demand, top-level sparring partner, which helped break many established thought patterns and raise the overall quality of decision-making in the field [250].

6. Reactive Navigation and Weather Routing

6.1. Central issues

Reactive navigation denotes short-horizon, sensor- or vision-driven decision-making that updates course, sail or wingsail trim, and maneuver timing on timescales of seconds to minutes. *Weather routing* is the long-horizon optimization of a time-parameterized route and speed profile, using gridded wind, current, and wave forecasts with vessel performance data, to optimize arrival time or other objectives over hours to days.

Sailboat path planning must account for both environmental forces and maneuver constraints, whose influence is far more pronounced than in engine-driven vessels. Wind-induced dead zones, nonholonomic dynamics, and right-of-way rules restrict feasible actions, while performance remains highly sensitive to spatiotemporal variability in wind and current (Figure 9). These directional and environmental constraints pose unique challenges for both reactive navigation and long-horizon weather routing.

1. **Dead zones and maneuver constraints:**

   Sailboats cannot sail directly into the wind and must employ zigzag maneuvers (tacking, Figure 9a) to make upwind progress. These maneuvers consume time and distance, and their effectiveness depends on inertia, heading angle, and wave effects. Moreover, in racing contexts, vessels must comply with regulatory right-of-way constraints, which impose additional limitations on maneuver freedom during tactical encounters.

2. **Sensitivity to environmental variability:**

   Wind and current conditions can change dramatically over time, especially in offshore or dynamic weather contexts. Because apparent wind angle directly affects both speed and feasibility, such changes may render previously optimal routes inefficient or entirely infeasible. Additionally, environmental interactions such as wind shadow (Figure 9b) interference from nearby vessels can amplify local performance degradation. These effects necessitate continuous replanning in both tactical navigation and long-horizon weather routing.

These challenges translate into distinct planning priorities across domains. For racing sailing, the focus lies in optimizing tacking sequences and long-term weather routing to minimize race time. Obstacle avoidance remains a critical task, but unlike general navigation, the "obstacles" are primarily other competing vessels. Accordingly, avoidance maneuvers are governed by right-of-way rules and are executed as part of tactical interactions. These often include deliberate positioning to constrain opponents' maneuvering options within rule-compliant boundaries [252].

In robotic sailing, the primary objective lies in long-range path planning, whether for reaching a designated destination with minimal time or for conducting coverage missions that require systematic traversal of large spatial areas. These tasks are typically performed under dynamic wind and current conditions, necessitating planning algorithms that account for both environmental variability and propulsion constraints. In addition, robotic sailboats must autonomously handle obstacle avoidance in both static and dynamic settings, due to the absence of human operators [253, 254].

6.2. Methodologies

As noted previously, reactive navigation and weather routing for sailboats cannot be classified into classic categories of local and global planning due to the unpredictable variability of the environment. Therefore, this paper categorizes the methods into two parts, including environment construction and path and trajectory generation. These methods can adapt to different planning scales by adjusting the size of the planning window. This paper offers a concise overview of selected algorithms relevant to sailing. For a more comprehensive discussion of path planning methods, the reader is encouraged to refer to [255, 256].

6.2.1. Environmental modeling and representation

Environment construction methods can be broadly categorized into grid-based, topological graph, and physics-informed graph approaches as shown in Figure 10. Grid-based methods (Figure 10a) are the most common in obstacle avoidance and weather routing. The simplest approach employs fixed-size grids, with each grid cell corresponding to an area linked to the sailboat's dimensions or its operational range, allowing movement in 4 or 8 directions [257, 258]. However, this method presents two challenges, including aligning wind fields and regions and accurately reflecting the anisotropic performance of sailboats. To address these, two improved grid techniques are used: grids reconstructed based on wind direction to ensure nodes align with reachable points in the competition area [252], and grids with more movement directions, which better capture sailboat kinematics [254, 259].

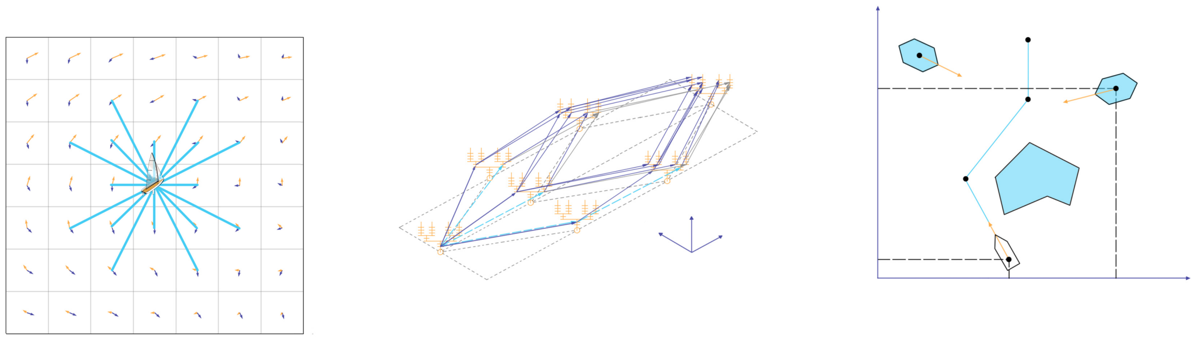
Topological graphs (Figure 10b) are typically employed in tacking timing and weather routing by discretizing the area or route into isochrones or a set of directed arcs and nodes [260]. Nodes often represent boundaries, checkpoints, or ports [261]. Unlike physics-informed graphs, these graphs do not incorporate physical dimensions, instead functioning as a representation of the process.

Physics-informed graphs (Figure 10c) are primarily used for obstacle avoidance. These graphs represent geometrical polygons derived from static obstacle shapes through geometric expansion or from dynamic obstacles considering relative positions, headings, and velocities. Such polygons may take forms like rectangles [262], ellipses [254], hexagons [263], or even more complex shapes [264].

6.2.2. Path and trajectory generation

Route generation methods can be classified in various ways, but in the context of reactive navigation and weather routing of sailing, four approaches are most commonly used.

Dynamic Programming, based on Bellman's principle of optimality [266], transforms multi-stage processes into sequential single-stage problems, making it particularly suitable for path generation in uncertain environments.



(a) Grid-based representation, with fixed grids supporting directional motion planning, adapted from [265].

(b) Topological graphs, abstracting routes into nodes and arcs for tasks like tacking and waypoint routing, adapted from [260].

(c) Physics-informed graphs, embedding obstacle geometry and vessel kinematics for accurate avoidance under static or dynamic conditions, adapted from [263].

Figure 10: Environmental modeling methods for sailboat navigation.

Artificial Potential Fields, introduced by Platonov in 1974, utilize virtual attractive forces near the target and repulsive forces near obstacles to guide movement along the gradient of the potential field. However, artificial potential field methods may encounter stagnation issues when attractive and repulsive forces counterbalance [267].

Search algorithms represent the most widely used approach, including classic methods such as Dijkstra and its heuristic-enhanced version A*, as well as optimization-based techniques like ant colony and particle swarm algorithms. These methods are computationally efficient and support multi-objective searches, although they require careful heuristic and objective function design [268, 263].

Lastly, reinforcement learning (RL) enables vessels to optimize decision-making strategies through continuous interaction with the environment, allowing them to adapt to complex and dynamic conditions without the need for explicit programming. However, these methods may struggle to generalize to previously unseen or rapidly changing scenarios [269, 258].

6.3. Contrasts and convergences

6.3.1. Racing sailing

In the racing branch, the primary goal of planning is not merely to reach a target quickly but to arrive faster than competitors, creating a positive time differential [252, 270, 171]. Weather inputs for racing sailing are typically highly accurate, derived from terrain-specific forecasts for a given venue [271, 272, 273], forecasts from high-resolution historical data [252], or represented as a Markov chain for probabilistic modeling [260]. Whether in inshore or offshore racing, the first task in planning is to determine the optimal zigzag angle to maximize the projected velocity toward the target, namely VMG. This optimal angle, typically ranging from 35° to 50° true wind angle (and often less for high-performance racing yachts), is usually calculated using the vessel's VPP, as illustrated in Figure 9 [252].

The second task involves path determination, which requires a tactical integration of tacking timing and weather routing considerations. On one hand, planners must account for environmental factors and anticipated changes that affect sailing speed. Tacking too early may require additional maneuvers, resulting in significant speed loss [173], while delaying tacking can lead to unnecessary distance traveled if wind conditions shift mid-maneuver [211]. On the other hand, the relative positions and interference between competing boats also play a critical role [274]. As illustrated in Figure 9, when two boats are in close proximity, wind affected by sails creates advantageous and disadvantageous zones (for more details, refer to Richards [275]). Decision-makers must leverage these dynamics to gain a competitive edge [107, 173, 276]. In such scenarios, the leading boat often adopts a robust strategy to maintain its position, while the trailing boat may opt for more aggressive tactics to overtake [172]. Given these complexities, reactive navigation and weather routing in racing sailing are often modeled as a topological graph. Decision-making processes typically employ dynamic programming [277, 252, 260] or RL approaches [211, 278] to obtain outcomes.

While establishing game-theoretic frameworks is theoretically vital, the practical implementation hinges on high-fidelity data acquisition and analysis. Future developments in competitive sailing may mirror the analytical rigor seen in top-tier esports titles such as *DOTA 2* and *CS:GO*, where victory relies less on abstract theory and more on granular replay parsing. By mining vast datasets to construct predictive tactical profiles of opponent behaviors, teams can anticipate strategies and counter-maneuver effectively.

6.3.2. Robotic sailing

In this subsection, we provide a brief overview of key navigation strategies in robotic sailing. For a more comprehensive treatment of the topic, readers are referred to recent surveys such as [69, 279].

Research on tacking timing remains limited, primarily because the focus is on the feasibility of upwind progress rather than optimizing windward efficiency. In current implementations, the maximum lateral displacement during a tacking maneuver is often predetermined rather than adaptively adjusted according to wind conditions [253, 233, 241]. Moreover, for small and slow autonomous sailboats, insufficient forward momentum may render tacking infeasible. In such cases, alternative strategies, such as replacing tacking with jibing, are adopted to maintain maneuverability [280].

Regarding obstacle-aware navigation and weather routing, most robotic sailing studies focus on static obstacle avoidance rather than tracking dynamic targets. Obstacle detection typically relies on vision systems [281, 282], LiDAR, or millimeter-wave radar [283], and is often integrated with rule-based decision systems [284] or potential field methods [281]. In some cases, static obstacle information is incorporated directly into weather-routing schemes [253]. Environmental inputs for these applications are commonly sourced from publicly available GRIdded Binary (GRIB) meteorological datasets [257].

Planning frameworks are typically grid-based, using either potential field navigation [285, 286] or search-based algorithms [268, 241] to generate feasible paths. Reinforcement learning is also increasingly applied to tasks involving dynamic obstacle avoidance and integrated decision-making under uncertainty [269, 258]. It is worth noting that due to the relatively low average speed of autonomous sailboats, their ability to traverse large regions efficiently is inherently limited. This makes two challenges particularly critical: (i) exploiting favorable ocean currents to minimize transit time, and (ii) achieving effective area coverage under spatiotemporally varying environmental conditions. Although global path planning has been widely studied for unmanned surface vehicles [287, 279], the unique constraints of wind-driven propulsion have received far less attention. As a result, these topics remain significantly underexplored in the context of autonomous sailboats, despite their central importance to long-range and persistent missions [288, 289].

6.4. Synthesis and transferability analysis

At the level of reactive navigation and weather routing, transferability is the weakest among the four topics. This primarily stems from the inherently competitive nature of racing. Strategies must simultaneously account for environmental factors and tactical interactions with competitors, which tightly couple reactive navigation and weather routing into a dynamic, sequential decision-making problem with game-theoretic characteristics. In contrast, robotic sailing typically decouples reactive navigation and weather routing into largely independent subproblems, treating them as separate path optimization tasks subject to motion and feasibility constraints (Table 5).

In environmental modeling and representation, methods from inshore course racing rarely translate to robotic sailing. First, racing research tends to model the contest as an evolving process rather than as a geospatial map in the robotic-sailing sense. Second, high-resolution, pre-race wind models [277] and the forward-looking wind cues obtained visually by human crews for reactive navigation are generally unavailable to autonomous platforms. Given that many oceanic events prohibit personalized meteorological assistance [290], their modeling assumptions align more closely with robotic sailing; in such offshore contexts, two-way methodological transfer is therefore plausible.

For path and trajectory generation, limited transferability again stems from the competitive nature of racing. Racing trajectories may deliberately exploit right-of-way rules to secure tactical advantage, whereas autonomous sailboats favor conservative, collision-free paths around both static and dynamic obstacles. Under identical environmental conditions, a trailing racer may adopt a more aggressive route, while an autonomous system prioritizes consistency and reliability. Likewise, exploiting wind shifts in racing remains largely driven by sailor expertise and intuition; although related techniques exist [291, 292, 293], they have yet to be applied to robotic sailboats, and current robotic platforms cannot perceive or predict ahead-of-boat wind changes from surface cues (e.g., wave patterns) with cameras or LiDAR at the level of an expert helm. Consequently, robotic implementations often rely on fixed cross-track distances for tacking and may gybe to compensate when upwind tacks are impeded. The most credible area of transferability is the point-to-point routing component in offshore races; however, competitive sensitivities limit public disclosure on the racing side, and the robotic literature remains sparse [294, 257].

Table 5: Transferability analysis of methods at the navigation-and-weather-routing level

Aspect	Environmental modeling and representation	Path and trajectory generation
Potential for transfer	Low	Low
Maturity leader	Racing	Racing
Main beneficiary	Both (limited cases)	Both (limited cases)
Current level of transfer	Low	Low
Main obstacles	Different assumptions Data scarcity	Mismatched objectives Tactical dependence

7. Shared Challenges and Research Opportunities

In the preceding sections, we mapped the contrasts and convergences between racing sailing and robotic sailing across key technical dimensions and examined the feasibility, as well as the principal obstacles, of cross-domain transfer. Nevertheless, several open problems persist across both domains, and there are technological opportunities that could substantially enhance knowledge and method-transfer. Advancing research along these lines is likely to benefit both communities.

7.1. Scalable and accessible component evaluation

High-precision component evaluation methods, developed primarily for established racing classes, have enabled accurate performance modeling through extensive experimental campaigns and curated databases. However, these methods are often costly, infrastructure-intensive, and tightly constrained by class-specific design rules, limiting their applicability beyond conventional platforms.

This presents a shared challenge for both unconventional racing yacht designs and autonomous sailboats, which increasingly demand cost-effective, adaptable evaluation tools to support diverse hull forms, appendages, and sail configurations. To address this gap, future efforts should focus on developing a generalized, variable-resolution evaluation framework capable of rapidly estimating aerodynamic and hydrodynamic performance, even in the absence of prior empirical data. Such a framework would reduce entry barriers, accelerate iterative design, and support innovation across sailing technologies.

7.2. Constructing kinetic models with tunable fidelity

Accurate kinetic models are essential for model-based control; yet, constructing such models remains a common challenge across both professional and autonomous sailing domains. High-fidelity dynamic models, such as those derived from DVPPs and CFD simulations, can capture detailed force—response relationships but require extensive prior data and significant computational resources. In control applications, such high-resolution modeling is often impractical, prompting the use of simplified dynamics as a compromise due to computational and real-time constraints.

To overcome this limitation, a key objective is to establish a standardized modeling pipeline that supports kinetic models with tunable fidelity. This pipeline should integrate scalable and accessible component evaluation techniques, standardized calibration and validation procedures, and principled simplification strategies that retain essential physical characteristics without degrading control performance.

7.3. Wave-inclusive performance assessment

Despite notable advances in overall performance modeling, current evaluation methods across both racing and autonomous sailing domains remain largely semi-quantitative. While they serve as valuable forecasting tools, their predictive accuracy is limited, particularly under complex sea conditions. A primary reason for this limitation is the insufficient treatment of wave-induced effects, which can degrade propulsion efficiency, destabilize attitude, and introduce significant planning errors, such as inaccurate arrival time estimation or infeasible routing choices.

Addressing this challenge requires the explicit integration of wave influences into both offline modeling frameworks and real-time navigation systems. This entails developing theoretical or data-driven models that capture performance degradation under various sea states, establishing correction strategies based on onboard wave recognition, and equipping control systems with adaptive mechanisms responsive to wave dynamics.

7.4. Weather routing in rapidly changing environments

Environmental awareness is critical for both tactical racing and autonomous navigation, as sailboats are inherently sensitive to short-term environmental fluctuations. Even minor changes in wind or wave conditions, on the scale of just a few boat lengths, can significantly affect feasible headings, propulsion efficiency, and route viability, requiring frequent adjustments to preplanned trajectories. However, current maritime forecasting systems are ill-equipped to support such fine-grained decision-making: offshore sailing still relies heavily on satellite-derived forecasts with coarse spatial (about 10 km) and temporal (3–6 hours) resolutions.

Bridging this gap requires advances along two complementary fronts. First, compact, deployable onboard sensors combined with short-term nowcasting algorithms are needed to deliver real-time awareness of local environmental conditions. Second, planning algorithms must be designed to accommodate rapidly changing inputs, either by explicitly modeling environmental uncertainty or by enabling robust online replanning.

7.5. Generalizing human sailing expertise

Despite notable progress in automatic control, current strategies for managing speed and heel remain suboptimal. Commercial and racing autopilots often operate reliably only in benign conditions, and robotic-sailing platforms frequently adopt conservative designs, such as overdesign for static stability, to avoid the risks associated with excessive heeling. While pragmatic, these choices inevitably cap attainable sailing speeds and reduce observational efficiency in long-range deployments.

By contrast, experienced sailors demonstrate exceptional adaptability in complex, rapidly evolving sea states. This gap underscores the potential of a complementary control paradigm: imitating the heuristics and decision patterns refined through centuries of seamanship. Leveraging such human expertise, via imitation learning, adaptive rule extraction, or human-in-the-loop adaptation, could substantially improve the agility, safety, and robustness of autonomous sailing, and, as part of intelligent training pipelines, may in turn inform and benefit elite racing.

8. Conclusion

Once eclipsed by the advent of steam propulsion, sailboats, vessels that served humanity for millennia, have witnessed a resurgence in recent decades. This revival, fueled by advances in fluid dynamics, navigation, communication, and meteorological forecasting, has given rise to two distinct yet complementary branches: racing sailing and robotic sailing. Despite their shared reliance on wind as a primary source of propulsion, the research communities surrounding these domains have remained largely siloed, limiting opportunities for cross-disciplinary exchange and innovation.

As an expert-led synthesis and perspective-driven review, this paper leverages cross-domain expertise to bridge this gap. We have systematically contrasted the differences and identified synergies between racing and autonomous sailing across four hierarchical technical dimensions: component-level performance evaluation, system-level performance estimation, motion control, and navigation and weather routing. Moving beyond a retrospective survey, we have provided critical analyses and forward-looking perspectives within each technical chapter.

To provide a structured mapping of cross-domain transferability within this hierarchy, we evaluate specific methodologies using a consistent five-metric framework. We systematically analyze the *potential for transfer* as dictated by the alignment of objectives and constraints, while determining the direction of technology overflow by contrasting the *maturity leader* with the *main beneficiary* of these cross-domain gains. Furthermore, by assessing the *current level of transfer*, we pinpoint the *main obstacles*, ranging from Reynolds number discrepancies to limited near-field awareness, that must be overcome to accelerate future convergence.

Ultimately, while this review cannot exhaust every specialized detail, it synthesizes the state of the art to foster mutual inspiration. Based on the shared challenges identified, we advocate for a unified research agenda focused on three critical frontiers: first, establishing unified modeling frameworks that balance precision with computational cost; such models possess cross-domain utility by serving simultaneously as high-fidelity performance evaluators for racing and agile maneuvering models for robotics. Second, enhancing perception and adaptability to spatiotemporal environmental variations, a shared necessity for refining racing performance prediction and strengthening autonomous control robustness. Finally, leveraging imitation learning to generalize human sailing heuristics; this approach transcends conservative automation for autonomous platforms and, in a reciprocal exchange, provides novel insights to inform professional sailor training. We anticipate that advancing these areas will not only catalyze the convergence of the racing and robotic communities but also provide the technological foundation essential for the next generation of sustainable wind-assisted shipping.

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CRediT authorship contribution statement

Yang An: Conceptualization, Writing (Original Draft, Review and Editing), Investigation and Visualization; **Jean-Baptiste R. G. Souppez:** Writing (Original Draft, Review and Editing) and Investigation; **Zhikang Ge:** Writing (Original Draft, Review and Editing); **Bo Peng:** Writing (Original Draft); **Mengwei Zhang:** Writing (Review and Editing); **Gaofei Xu:** Writing (Review and Editing); **Zhengru Ren:** Supervision and Writing (Review and Editing).

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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