

Review

Digital Twins for Marine Robotic Platforms: Architectures, Applications, and Challenges Across AUVs, ROVs, USVs, Underwater Gliders, and Emerging Platforms

Xuehao Wang ^{1,2} , Linzhi Chen ¹, Dongyang Xue ¹ , Cheng Chen ^{1,*} and Peng Wang ²¹ School of Mechanical Engineering, Tianjin University of Commerce, Tianjin 300134, China; xuehaowang@tjcu.edu.cn (X.W.)² Key Laboratory of Mechanism Theory and Equipment Design of Ministry of Education, School of Mechanical Engineering, Tianjin University, Tianjin 300354, China

* Correspondence: cc@tjcu.edu.cn

Abstract

Digital twin (DT) research spans autonomous underwater vehicles (AUVs), remotely operated vehicles (ROVs), unmanned surface vessels (USVs), underwater gliders, and emerging marine robotic platforms; however, reported systems differ widely in terms of their physical–virtual coupling and validation maturity. A structured Web of Science search retrieved 116 records, of which 107 were retained for analysis. This review synthesizes architectures, enabling technologies, applications, coupling modes, validation settings, and deployment barriers across the perception–decision–control chain. The reported workflows address model construction, multiphysics simulation, virtual testing, monitoring, control validation, and decision support. Within the purposively selected 11-case full-text audit, two cases were classified as DT-enabling methods or components, five as digital models or virtual prototypes, three as digital shadows, and one as a bidirectional DT prototype; none documented sustained operational deployment. Four constraints recurred across platforms: the trade-off between model fidelity and computation; uncertain marine environments; communication and synchronization limitations; and fragmented interfaces and standards. Physics-informed learning, multi-fidelity modeling, edge computing, and interoperable reference architectures provide candidate development paths, but the evidence suggests that the central gap lies less in producing sophisticated virtual models than in establishing sustained, interoperable, and bidirectional physical–virtual operation.

Keywords: marine robotics; marine digital twin; AUV; ROV; USV; underwater glider; edge computing



Academic Editor: Vincenzo Crupi

Received: 24 June 2026

Revised: 23 July 2026

Accepted: 27 July 2026

Published: 29 July 2026

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1. Introduction

The ocean, which covers 71% of the Earth's surface, represents a vast repository of resources, energy, transportation networks, and strategic assets. Marine robots, including autonomous underwater vehicles (AUVs), unmanned surface vessels (USVs), and remotely operated vehicles (ROVs), are used to explore, monitor, and operate in the marine environment. However, the dynamic nature, high pressure, and limited communication capabilities of the ocean pose significant challenges to the design, testing, operation, and maintenance of these robotic systems.

Digital twins (DTs) provide a framework for relating a physical marine robot to one or more virtual representations through data exchange. Depending on the implemented

connection, DT-related workflows can support design verification, operational monitoring, prediction, or decision support. These capabilities are relevant to marine robots because field testing is costly and physical models must contend with uncertain hydrodynamics, restricted communication, and safety-critical operation. The presence of a detailed simulator alone, however, does not establish a digital twin.

In this review, the term digital model/virtual prototype denotes a virtual representation without automated online exchange with a physical asset. A digital shadow receives automated $P \rightarrow V$ data but does not report an automated $V \rightarrow P$ decision or control return path. A bidirectional DT prototype additionally reports online physical–virtual state or control exchange in a laboratory, hardware-in-the-loop (HIL), or field prototype. Operational DT is reserved for automated bidirectional synchronization demonstrated during repeated missions or sustained operation beyond a one-off laboratory or field prototype. This operational distinction follows established data integration taxonomies and recent maritime classification work [1,2].

Although legacy multibody, hydrodynamic, and environmental simulators can serve as DT-enabling components, their evidential role depends on how they are connected to physical data and operations. Offline calibration, software-in-the-loop (SIL), and HIL testing may improve model credibility or reduce development risk, but do not by themselves establish an operational DT. This distinction is especially relevant to marine robotics, where a physically tested model may still be updated only after a trial, while a closed control loop may exist entirely within a virtual environment.

Marine robots used for resource exploration, environmental monitoring, and maritime safety must operate in dynamic, interference-prone, and weakly structured underwater environments. Recent reviews have predominantly examined individual technical themes, including navigation and control [3,4], biomimetic design [5–7], and perception and sensing [8,9]. These studies provide important technical insights, but do not systematically compare how physical–virtual coupling, model updating, validation maturity, and operational feedback interact across different marine robotic platforms.

Marine robots operate under high pressure, restricted visibility, biofouling, uncertain currents, and limited communication, which complicate modeling, validation, and control [10,11]. DT-related workflows may support virtual testing, monitoring, and decision support, but evidence for real-time bidirectional deployment remains limited. Therefore, this review examines the reported functions, coupling modes, and deployment constraints of DT-related systems across marine robotic platforms.

Considering the main objective of this review, one overarching research question (RQ) and three sub-questions (SQs) are formulated:

RQ. What are the recent developments in the practical application of digital twin technology in the field of marine robotics?

SQ1. What are the key functional modules and enabling technologies that underpin digital twin platforms for marine robots across the perception–decision–control chain?

SQ2. How have digital twins been applied to different types of marine robots (e.g., AUVs, USVs, ROVs) and lifecycle stages (design, operation, maintenance) in representative ocean missions?

SQ3. What are the main technical and environmental challenges that currently limit DT deployment in marine robotics, and what trends can be foreseen for future research and development?

Existing reviews of marine robotics predominantly focus on individual technical areas such as navigation and control, bio-inspired design, or perception and sensing, often treating modeling and simulation as offline design tools. By contrast, structured analyses of how digital

twins can integrate these technologies into a cohesive perception–decision–control pipeline for marine robots remain scarce. This paper addresses this gap by:

1. Establishing an evidence-based distinction among DT-enabling components, digital models/virtual prototypes, digital shadows, bidirectional DT prototypes, and operational DTs in marine robotics.
2. Structuring the key functional modules and enabling technologies of DT platforms tailored to marine robots.
3. Synthesizing recent DT applications across robot types, lifecycle stages, and mission scenarios.
4. Identifying domain-specific challenges and future research trends for DT-enabled marine autonomy.

2. Methodology

This structured literature review uses a reproducible search, staged eligibility screening, and evidence-role coding to examine DT-related research in marine robotics. The protocol distinguishes records returned by the search from studies retained for evidence synthesis and separates robot-centered evidence from the contextual or technology-enabling literature.

2.1. Protocol

The review followed a three-step protocol comprising literature collection, eligibility screening, and data extraction and classification.

Step 1—Literature collection. The Web of Science (WoS) Core Collection was searched on 10 July 2026 using an eligible publication window of 2004–2026. The search was restricted to English-language journal articles and proceedings papers.

Web of Science Core Collection query: TS = (("autonomous underwater vehicle*" OR "remotely operated vehicle*" OR "remotely operated underwater vehicle*" OR "unmanned underwater vehicle*" OR "uncrewed underwater vehicle*" OR "hybrid autonomous underwater vehicle*" OR "underwater glider*" OR "autonomous underwater glider*" OR "autonomous surface vehicle*" OR "unmanned surface vehicle*" OR "uncrewed surface vehicle*" OR "autonomous surface craft*" OR "unmanned surface craft*" OR "autonomous marine vehicle*" OR "unmanned marine vehicle*" OR "uncrewed marine vehicle*" OR "marine autonomous system*" OR "marine robot*" OR "underwater robot*" OR "subsea robot*" OR "ocean robot*" OR "underwater drone*" OR "marine drone*" OR "robotic fish" OR "soft underwater robot*" OR "soft marine robot*" OR "bio-inspired underwater robot*" OR "bioinspired underwater robot*" OR ((AUV OR AUVs OR ROV OR ROVs OR UUV OR UUVs OR USV OR USVs OR ASV OR ASVs OR AUG OR AUGs OR HAUUV OR HAUUVs) AND (marine OR maritime OR ocean* OR underwater OR subsea OR glider* OR "surface vessel*"))) AND ("digital twin*" OR "digital shadow*" OR "virtual twin*") AND LA = (English) AND DT = (Article OR Proceedings Paper).

The search returned no records published before 2018; therefore, the observed publication span of the retrieved set was 2018–2026. This lower bound arose from the records returned by the optimized query rather than from an additional post hoc year restriction. Thus, the retrieved set represents studies explicitly indexed using digital twin terminology.

Step 2—Eligibility screening. The optimized query returned 116 records. Checks of titles and available DOI values identified no duplicates, and all 116 records proceeded to title–abstract screening. One author performed the initial screening against the predefined eligibility criteria; a second author reviewed the screening decisions and all borderline records. Full texts were consulted when the title and abstract did not provide sufficient information for an eligibility decision. Disagreements were resolved through discussion. Screening retained 107 records for corpus-level analysis and evidence-role coding. Nine records were excluded.

A complete record-level registry of all 116 records retrieved by the Web of Science search is provided in Supplementary Data S1. For each record, the registry reports a stable record identifier, authors, title, publication year, document type, source title or conference, DOI and URL when available, final eligibility status, and for excluded records, the record-specific reason for exclusion. The registry separately identifies the 107 retained records and nine exclusions. The study-level basis for the totals is reported in Figure 1 and Table 1. The reference list contains the works cited in the manuscript, and is not intended to serve as the registry of all records assessed during screening.

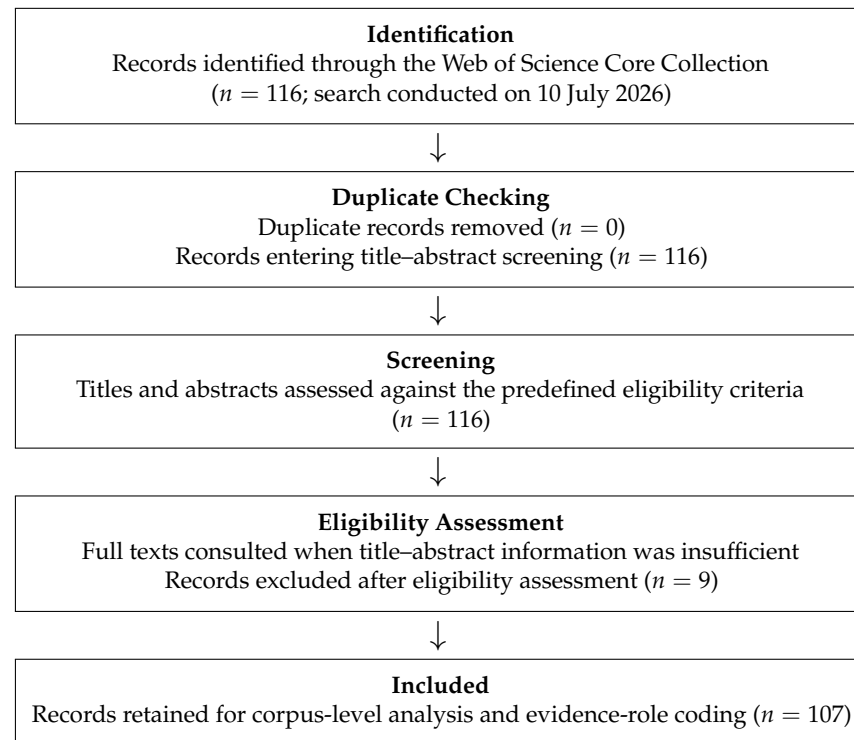


Figure 1. Study selection flow for the optimized Web of Science search. The diagram distinguishes identification, duplicate checking, title–abstract screening, conditional full-text eligibility assessment, exclusion, and final inclusion. Detailed reasons for the nine excluded records are provided in Table 1. Source: authors’ schematic.

Inclusion criteria. Records were retained as direct evidence when: (i) a marine robotic platform such as an AUV/UUV, ROV, USV/ASV, underwater glider/AUG, or emerging underwater robot was the primary system or mission platform; and (ii) a DT or DT-enabled workflow was implemented for modeling, virtual testing, sensing, synchronization, monitoring, decision support, or control of the platform or its mission-specific onboard systems. Records were retained as contextual or technology-enabling evidence when they reported marine operational sensing methods, validation infrastructure, or asset-level DT workflows with explicit relevance to marine robotic deployment, although the robot itself was not the twinned asset. These contextual records were not used as direct evidence of robot-centered physical–virtual coupling or operational maturity.

Exclusion criteria. Records were excluded when: (i) the primary application was non-marine; (ii) a marine robot was mentioned only prospectively or incidentally and did not contribute data, validation, or operation to the reported DT workflow; (iii) DT was presented only as a future direction without an implemented model, workflow, or validation infrastructure; or (iv) neither a DT-enabled nor a virtual–real workflow was described. No record was excluded solely because its title contained terms such as machine learning, deep learning, algorithm, or control.

Table 1. Study selection and exclusion summary for the optimized Web of Science search.

Item	Record or Screening Stage	Decision, Reason, or Analytical Role
S1	Records returned by the exact WoS query ($n = 116$)	All records entered title–abstract screening.
S2	Duplicate removal ($n = 0$)	No duplicate titles or duplicate DOI values among records with an available DOI were identified.
S3	Records excluded after screening ($n = 9$)	The excluded records and record-specific reasons are listed below (E1–E9).
S4	Records retained for analysis ($n = 107$)	Retained records comprised direct marine robotics evidence and separately coded contextual or technology-enabling evidence.
E1	Automated 2D, 2.5D, and 3D Segmentation of Coral Reef Point-clouds and Orthoprojections	The digital twin represented a coral reef site; UUV data collection was discussed only as a future development.
E2	Research on Structural Health Assessment Methods for Long-Distance Underground Culverts under Multi-Source Data Collaboration	The primary application was non-marine infrastructure.
E3	Research Progress and Development Prospects of Dynamics Theory and Vibration Control of Mining String Used in Oil & Gas Exploration for Deep Sea	The mining string was the primary asset, and a robot-centered DT workflow was proposed only as future work.
E4	Single and Multiphase Flow Leak Detection in Onshore/Offshore Pipelines and Subsurface Sequestration Sites: An Overview	The pipeline was the primary asset; an ROV was mentioned only as an alternative inspection method.
E5	Robot Online Learning through Digital Twin Experiments: A Weightlifting Project	The robotic application was non-marine.
E6	Toward Smart Aquaculture: A Review of Multimodal Methods, Datasets, and Applications from the Modality Perspective	DT integration was identified as a future trend rather than an implemented marine-robotics DT workflow.
E7	Creating a Remote Access-Ready Infrastructure for the Future	The study described remote marine robotics infrastructure but did not report a DT or virtual–real workflow.
E8	Towards a Digital Twin for a Drinking Water Source in Norway	The twinned asset was a freshwater reservoir rather than a marine system.
E9	Underwater Human–Robot and Human–Swarm Interaction: A Review and Perspective	The study did not report a DT or virtual–real workflow.

The identification, duplicate-checking, screening, eligibility, and inclusion stages are summarized in Figure 1, while Table 1 reports the record-specific reasons for exclusion.

Step 3—Data extraction and classification. Two levels of data extraction were used. First, for all 116 records returned by the search, publication year, document type, publication source, and one primary platform or application-context category were recorded from the indexed metadata, titles, and abstracts. These fields were used only for the retrieval-level descriptive summaries reported in Section 2.2.

Second, for the 107 records retained after eligibility screening, the extraction framework additionally covered lifecycle context, DT functional role, enabling technical approach, application or mission context, and evidence role. Evidence role was coded separately from physical–virtual coupling and validation so that contextual or technology-enabling literature did not increase the apparent maturity of robot-centered DTs. For records used to support study-level claims, full texts were additionally reviewed to extract physical data sources, virtual model basis, physical–virtual coupling direction, communication and update mode, validation setting, deployment context, and reported limitations.

Figure 2 provides a conceptual overview of the representative platforms, functional links, and enabling components used to organize the subsequent analysis.



Figure 2. Conceptual map of representative marine robotic platforms and their supporting cyber-physical functions. The central layer shows representative AUV/UUV, underwater glider, ROV, and USV/ASV platforms. The inner ring summarizes communication, computation, control, and information processing, while the outer layer illustrates representative sensing, communication, computing, and actuation components. Source: authors' schematic.

Of the 107 retained records, 92 were assigned to a platform-focused candidate pool during title–abstract coding: 43 USV/autonomous-ship records, 21 AUV/UUV records, 10 ROV/teleoperated records, 8 emerging underwater robot records, 6 underwater glider records, and 4 multi-platform records. The remaining 15 retained records were coded as marine environment/infrastructure ($n = 9$) or generic/adjacent ($n = 6$), and were not included in the platform-focused case-selection pool.

For the retrieval-level platform or application-context classification, each record was assigned one primary category according to the principal system or context examined in the title and abstract. The categories were AUV/UUV, ROV/teleoperated system, USV/autonomous ship, underwater glider, emerging underwater robot, multi-platform study, marine environment/infrastructure, and generic/adjacent study. A record was coded as multi-platform only when more than one marine robotic platform formed a substantive part of the study, rather than when another platform was mentioned incidentally.

For the technical axis cross-tabulation, each retained record was assigned one dominant technical axis according to its principal objective, method, and reported technical contribution. The seven axes were overall design and architecture; hydrodynamics and performance; structural strength and integrity; navigation, guidance, and control; energy and propulsion; mission payload and perception; and operations, maintenance, and assurance. Therefore, the quantitative platform distribution and technical axis cross-tabulation

use one primary code per analytical dimension; records were not counted in more than one cell of the same figure.

The platform/application context and dominant technical axis classifications were assigned manually by one author from the indexed metadata, titles, and available abstracts using the category definitions above. Software was used only to tabulate the author-assigned categories, and did not determine the classifications.

2.2. Status Analysis

The publication year, document type, source, and platform or application context summaries reported in this subsection describe all 116 records returned by the revised Web of Science search. The substantive evidence synthesis is restricted to the 107 records retained after eligibility screening. The technical axis cross-tabulation across platform or application context categories includes 101 of the 107 retained records, as explained below.

The retrieved set covers 2018–2026, with four records from the partially covered year of 2026. The annual publication counts were 2 in 2018, 0 in 2019, 4 in 2020, 3 in 2021, 15 in 2022, 21 in 2023, 22 in 2024, 45 in 2025, and 4 in 2026. Records published during 2022–2025 accounted for 103 records, or 88.8% of the retrieved set, whereas nine records were published during 2018–2021, as shown in Figure 3. This distribution indicates that the literature captured by the optimized query is concentrated in recent years.

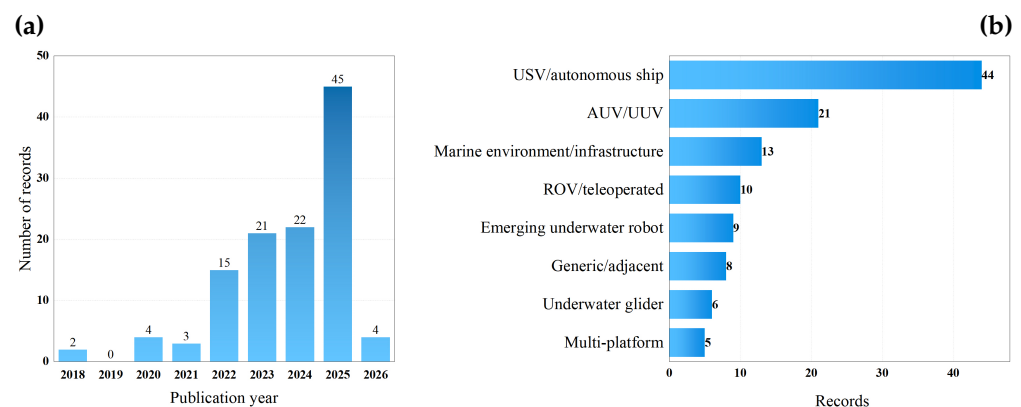


Figure 3. Publication year and platform or application context distributions of the 116 records retrieved through the revised Web of Science search. (a) Annual numbers of retrieved records; 2026 is a partially covered year because the search was conducted on 10 July 2026. (b) Primary platform or application context category assigned to each record from its indexed metadata, title, and abstract. Each record contributes to one category. Both panels describe the retrieved corpus rather than the 107 records retained after eligibility screening. Source: authors' analysis of the Web of Science records.

The retrieved set comprises 75 journal articles and 41 conference papers. Among the journal venues, *Ocean Engineering* contributed the largest number of records (14), followed by the *Journal of Marine Science and Engineering* (5) and *IEEE Access* (4). The 20 most frequent journal titles account for 50 records, corresponding to 66.7% of all journal articles and 43.1% of the 116-record retrieved set. The source distribution spans ocean engineering, marine science, robotics and control, sensing, and engineering informatics. The 15 most frequent sources, each represented by at least two records, are summarized in Figure 4.

The platform or application-context distribution of the 116 retrieved records comprised 44 USV or autonomous ship records, 21 AUV/UUV records, 13 marine environment or infrastructure records, 10 ROV or teleoperated system records, 9 emerging underwater robot records, 8 generic or adjacent records, 6 underwater glider records, and 5 multi-platform records. These categories describe the retrieved set.

Figure 5 cross-tabulates the dominant technical axis and primary platform or application-context category of the retained records. The matrix includes 101 of the

107 records retained after eligibility screening. Each record contributes to one cell only. Six retained records coded as generic or adjacent contextual evidence were omitted because they were not assigned to one of the seven platform or application context categories represented in the matrix; these records remain part of the 107-record evidence corpus.

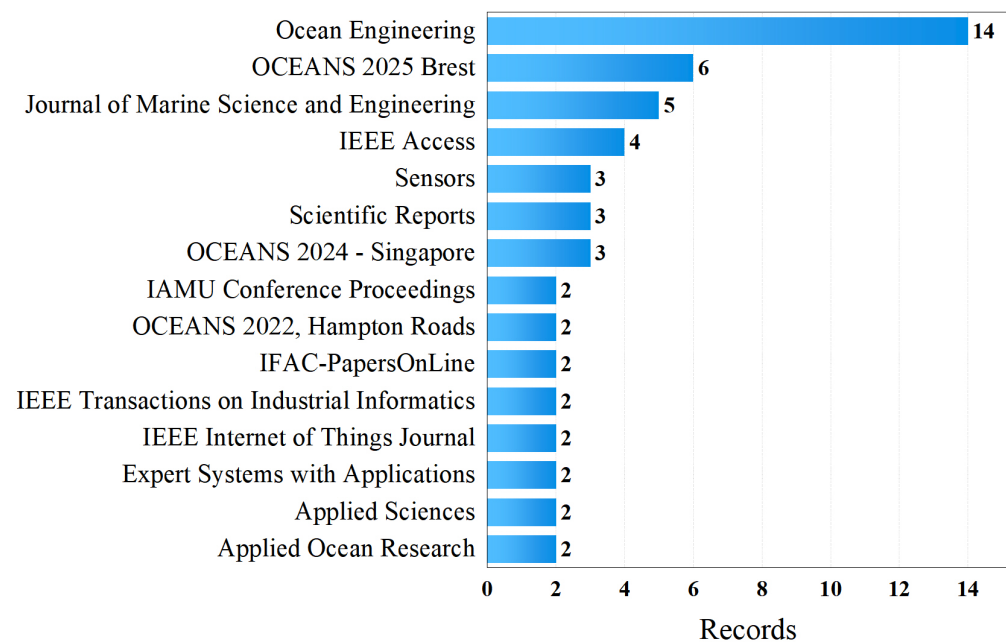


Figure 4. Leading publication sources in the 116-record Web of Science retrieval corpus. Bars show the number of retrieved records for the 15 most frequent sources, each represented by at least two records. Journal titles and conference proceedings series are reported as indexed in Web of Science. The counts were tabulated directly from the publication source field in the Web of Science export. Source: authors' analysis of the Web of Science records.

Review scope and methodological limitations. This review used the Web of Science Core Collection as its sole bibliographic database, and was restricted to English-language journal articles and proceedings papers. Consequently, relevant studies not indexed in Web of Science, including records available primarily through Scopus, IEEE Xplore, or other specialized databases may not have been captured; studies published in languages other than English may also not have been captured. The search also required explicit use of the terms “digital twin”, “digital shadow”, or “virtual twin”. Earlier or functionally related work described instead as cyber-physical systems, virtual prototyping, simulation, hardware-in-the-loop testing, or model-based monitoring may fall outside the retrieved corpus. In addition, because the search was conducted on 10 July 2026, the 2026 publication count represents only partial-year coverage. Indexed metadata, titles, and abstracts were used for part of the screening and classification, while full texts were consulted when eligibility could not be determined from these fields and for the study-level evidence audit. The descriptive platform/application context and technical axis classifications were assigned by one author, which introduces judgment-related classification uncertainty. Accordingly, the reported distributions and classifications characterize the literature retrieved under the specified protocol and should not be interpreted as an exhaustive inventory of all functionally related research in marine robotics.

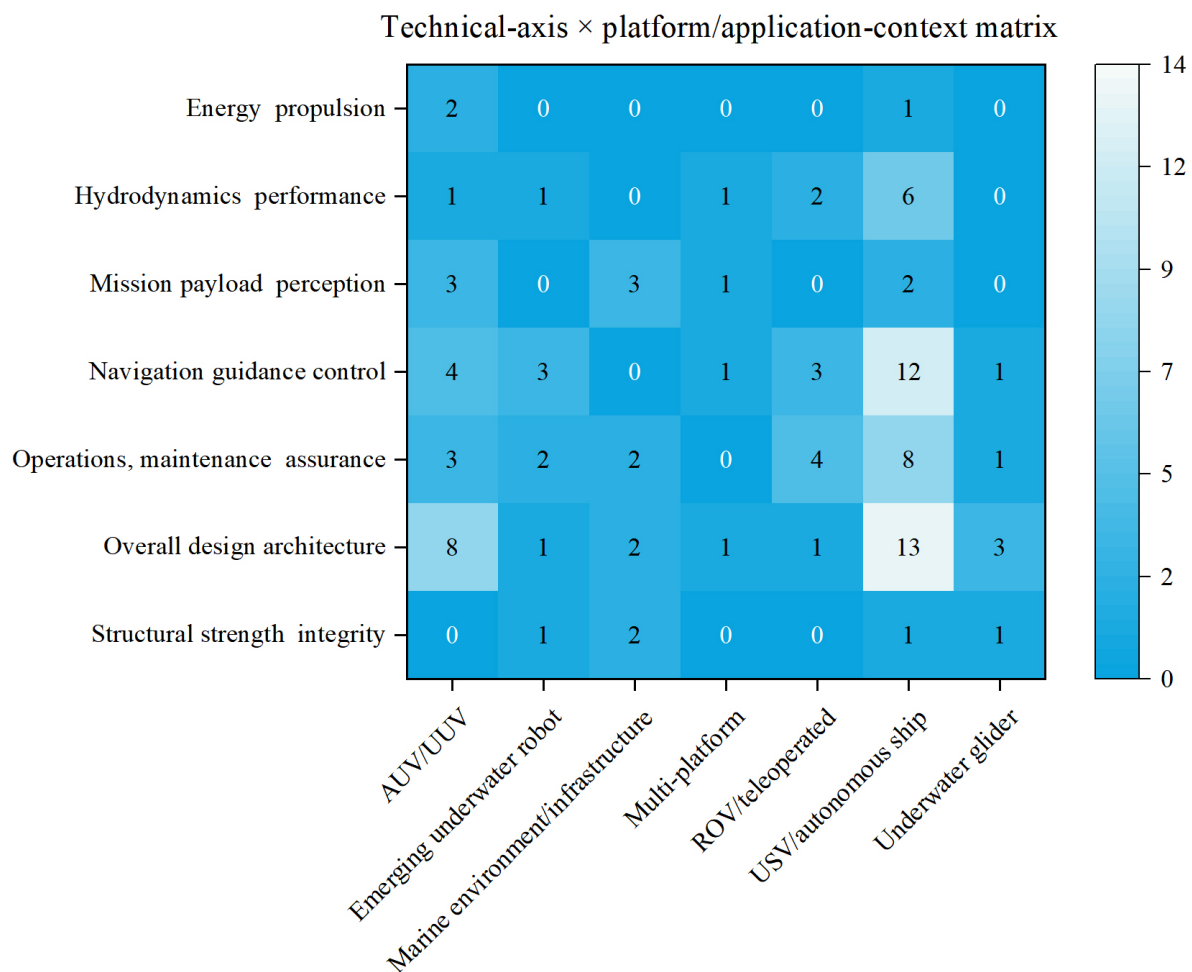


Figure 5. Technical axis cross-tabulation across platform or application context categories for 101 of the 107 records retained after eligibility screening. Each cell reports the number of retained records assigned to the corresponding combination of one dominant technical axis and one of seven platform or application-context categories. Six retained generic or adjacent contextual records were excluded because they were not assigned to one of the seven categories represented in the matrix. Cell counts sum to 101. Source: authors' descriptive tabulation of the record-level classifications provided in Supplementary Data S1.

2.3. Digital Twin Concept

Digital twins are virtual representations associated with physical entities through data exchange and multidisciplinary models. The direction, automation, and continuity of that exchange determine whether a reported workflow is classified as a digital model/virtual prototype, a digital shadow, a bidirectional DT prototype, or an operational DT. At higher levels of integration, the virtual representation can support diagnosis, prediction, decision support, and control across the asset lifecycle; these functions alone, however, do not establish sustained bidirectional operation. By diagnosing, analyzing, and predicting these digital models, decision-making and control of the physical entities can be optimized throughout their lifecycle, ultimately fostering shared insights and collaborative development between the physical and digital realms.

The digital twin software model can be expanded into a six-dimensional framework, in which physical and virtual entities are typically distinguished through graphical user interfaces (GUIs) and other visualization tools. The virtual entity, defined by software, is developed around the data (DD) exchanged between the physical entity (PE) and the

study. A DT-enabling method/component provides a model, solver, sensor, communication mechanism, or development method without forming a complete digital twin workflow. A digital model/virtual prototype lacks automated online physical–virtual exchange; a closed loop confined to simulation remains in this category. A digital shadow reports automated $P \rightarrow V$ updating without a reported automated $V \rightarrow P$ decision or control path. A bidirectional DT prototype reports online $P \leftrightarrow V$ state or control exchange and synchronization in a laboratory, HIL, or field prototype. Operational DT is reserved for repeated or sustained operation with automated bidirectional synchronization.

Here, “online” denotes data exchange while a system is operating, and does not by itself imply bounded latency; “real-time” is used only when the cited study explicitly reports timing-constrained computation or exchange; “repeated” denotes more than one reported mission or deployment; and “sustained” denotes operation maintained over a reported mission or duration. Accordingly, neither repeated testing nor sustained one-way monitoring alone is sufficient for classification as an operational DT.

Validation was coded separately as the following categories: simulation only, laboratory/HIL prototype, field/sea-trial prototype, or repeated operational deployment. From the 92 platform-focused candidates, 11 cases were purposively selected for full-text audit. Eligibility for the case audit required that the full text provide sufficient information to assess the physical data source, virtual model basis, direction and automation of physical–virtual exchange, communication or update mode, validation setting, deployment context, and reported limitations. Selection sought qualitative variation across the five focal platform groups, lifecycle functions, physical–virtual coupling patterns, validation settings, and evidence classes.

The resulting case set comprised three AUV/UUV cases, two ROV cases, three USV/ASV cases, one underwater glider/AUG case, and two emerging soft or tracked underwater robot cases. No multi-platform record was included in the audited case set. The cases were selected to illustrate contrasting technical configurations rather than to constitute a statistically or proportionally representative sample of the 92 platform-focused candidates or the 107 retained records. Consequently, evidence class counts and operational maturity conclusions derived from this audit are restricted to the 11 cases, and are not interpreted as corpus-wide prevalence estimates.

Table 2 reveals three distinctions that are obscured when studies are grouped only according to the authors’ use of the DT label. First, physical testing does not by itself establish an operational DT: Li et al. [12], Orjales et al. [13], Cho et al. [14], and Mathew et al. [15] used experiments to train, calibrate, or validate models without maintaining an automated bidirectional connection during the reported workflow. Second, a closed loop within simulation is not physical–virtual coupling: Wen et al. [16] and Berg et al. [17] exchanged states, parameters, or commands among virtual modules, but did not connect the evaluated loop to a physical vehicle. Third, Bhagavathi et al. [18], Xia et al. [19], and Scaradozzi et al. [20] all reported physical-to-virtual monitoring or operator-facing feedback, placing them closer to digital shadows under the adopted criteria. Within the 11-case full-text audit, only Yu et al. [21] reported online bidirectional state or control exchange with field validation, while repeated or sustained operational deployment was not reported.

Table 2. Evidence matrix for the 11 marine robotics cases purposively selected for full-text auditing, mapped by their platform, lifecycle context, DT function, physical–virtual coupling, validation setting, deployment context, evidence class, and main limitation.

Study	Platform and Mission	Lifecycle Context	DT Function	Physical Data and Virtual Model Basis	Coupling, Communication, and Update Mode	Validation and Deployment Context	Evidence Class and Main Limitation
AUV/UUV							
Kutzke et al. [22]	UUV; subsystem selection	Design and development	M1, M4	Experimentally determined cost/reliability metrics from a real-UUV system model	Offline inputs; communication, automatic updating, and feedback path NR	UUV analytical case study; integrated twin validation NR	DT-enabling method/component; selects candidate subsystems but does not implement a connected twin
Li et al. [12]	AUV; motion control	Virtual testing and verification; Mission operation and control	M1, M2, M4	Velocity/control samples; physics-informed dynamics model	Offline P→V dataset, then one-time V→P controller transfer; no continuing link	Simulation and controlled pool tests; Laboratory prototype	Digital model/virtual prototype; sim-to-real transfer without sustained synchronization
Orjales et al. [13]	Open-frame AUV/ROV; hydrodynamic identification	Design and development; Virtual testing and verification	M1, M2	Experimental trajectories; calibrated 6-DOF hydrodynamic model	Offline/iterative P→V calibration; operational return path NR	Controlled BlueROV2 tests; Laboratory prototype	Digital model/virtual prototype; validated model, not an online twin
ROV							
Xia et al. [19]	ROV; augmented teleoperation	Mission operation and control; Training and human interaction	M4, M5	ROV environmental/spatial sensor data; Gazebo/Unity workplace model	Online P→V data augmentation with visual/haptic feedback to the operator; transport details NR	VR/haptic evaluation; integrated field deployment NR; Laboratory/HIL prototype	Digital shadow concept; human feedback is not an automated V→P return path
Scaradozzi et al. [20]	ROV; inspection navigation	Mission operation and control	M3, M5	USBL position and vehicle attitude; dynamic/Unity model	Online P→V via tether, USBL, ROS, and Unity; automated DT-generated return command NR	Port tests and trajectory comparison; Field/port prototype	Digital shadow prototype; bidirectional integrated-twin validation not reported
USV/ASV							
Bhagavathi et al. [18]	ASV; actuator-fault diagnosis	Monitoring and diagnosis	M4, M5	GNSS/control data; graphical vessel model and adaptive EKF	Online P→V estimation and web visualization; automatic control return NR	Otter ASV sea trials; field/sea trial prototype	Digital shadow; diagnosis is available for control but no automated V→P path is shown
Berg et al. [17]	ASV; controller and parameter adaptation	Virtual testing and verification; Mission operation and control	M1, M2, M4	Simulated vessel states; NMPC model and DRL parameter estimator	Closed-loop parameter updating within V; physical vessel data stream absent	Numerical experiments; Simulation only	Digital model/virtual prototype; real-world validation identified as future work
Yu et al. [21]	Multi-USV; formation-control verification	Virtual testing and verification; Mission operation and control	M3, M4, M5	Longitude, latitude, velocity, and heading; Unity3D vessel/environment models	Online P↔V state/control exchange via TCP/IP/serial links with clock and spatial synchronization	Physical–virtual experiments in real sea conditions; Field/sea trial prototype	Bidirectional DT prototype; repeated missions and sustained operation NR
Underwater glider/AUG							
Wen et al. [16]	Multi-AUG; formation and path planning	Virtual testing and verification	M2, M4, M5	Gazebo-generated attitude/position states; AUG and ocean-current models	V-only Gazebo–ROS–WebGL exchange; no physical AUG data stream	MATLAB and Gazebo experiments; Simulation only	Digital model/virtual prototype; reported “real” states are physics engine outputs
Emerging soft or tracked underwater robot							
Cho et al. [14]	Tracked underwater robot; terrain-contact solver	Design and development; Virtual testing and verification	M1, M2	Track/terrain test data; real-time contact model and MBD reference	Offline validation of a candidate real-time component; integrated CPOS/HILS link NR	Controlled land-based tests; Laboratory prototype	DT-enabling method/component; underwater integrated twin validation remains future work
Mathew et al. [15]	Soft underwater robot; maneuvering and control	Design and development; Virtual testing and verification	M1, M2, M4	Depth/IMU feedback and actuator commands; Cosserat rod model	Model and prototype evaluated separately; automated online P↔V exchange NR	Physical prototype experiments; Laboratory prototype	Digital model/virtual prototype; local robot feedback is not twin synchronization

3. Key Technologies

3.1. Key Functional Modules

Building on the operational definition in Section 2, we decompose marine robotics DT workflows into five functional modules: M1, twin model construction and management; M2, multiphysics simulation and virtual experimentation; M3, physical–virtual synchronization and control; M4, intelligent analysis and decision support; and M5, visualization and interaction. These modules describe functional roles rather than maturity levels. A study may implement M1 or M2 as a DT-enabling component without automated physical–virtual coupling, whereas M3 requires explicit evidence of synchronization and data flow direction. M4 and M5 may operate in a digital shadow when analytics or visualization receive physical data but do not automatically return decisions to the robot.

For module (i), automated geometric and physical modeling extends static virtual representations toward models that can be updated or queried during DT-related workflows. Despite these innovations, the complexity of parametric configurations still limits the accuracy of multiphysics field coupling. High-fidelity geometric modeling requires intelligent parsing and topological reconstruction of CAD models. For instance, the blended wing–body underwater glider (BWBUG) achieves a fluid-optimized shape via parametric surface fitting, while the AUV support platform employs proper orthogonal decomposition (POD) to dynamically extract high-energy eigenvectors, reducing a finite element model with millions of elements into a simplified equation for real-time computation. Although this automation can accelerate model construction, incomplete material property data and nonlinear material behavior, including metal fatigue and composite anisotropy, can reduce the accuracy of structural deformation predictions under extreme marine conditions.

For module (ii) and its coupling to (iii), heterogeneous integration strategies for simulation engines improve dynamic computation efficiency but expose a fundamental trade-off between physical fidelity and real-time performance. The prevalent method involves co-simulation by integrating ADAMS with MATLAB. This approach has been used for the dynamic optimization of a hyperboloid cam piston engine for AUVs, aligning with experimental data [23]. Additionally, the ADAMS-Simulink platform validated the effectiveness of position–velocity closed-loop control for an AUV underwater docking system [24]. For reinforcement learning development, the Yara ocean virtual environment combines Gazebo with a lift–drag model derived from a physical sailing robot. The study reports a 300-fold simulation speedup on a laptop equipped with an Intel i7 processor, 8 GB RAM, and an NVIDIA RTX 3060, allowing one million training time steps to be completed in approximately eight hours [25]. This value characterizes simulator throughput under the reported hardware and model configuration; it should not be interpreted as a general acceleration factor for marine DTs or HIL systems. However, HIL verification remains limited. In USV autonomous navigation tests, although ROS-driven HIL simulation mitigates risks associated with full-scale vessel tests [26], motor response delays cause a time mismatch between control commands and dynamic feedback [27], underscoring challenges in digital thread synchronization.

Focusing on module (iv) and its interface with (v), data management architectures are evolving from passive storage to active decision support. As contextual rather than robot-centered evidence, [28] reports a digital twin for which the twinned asset is the Trondheim Fjord water quality system. Its time series database, event-driven algal bloom alerts, and Unity–Cesium visualization illustrate marine environment data management and visualization, but are not used here as evidence of physical–virtual coupling or operational maturity for a marine robot. By contrast, the digital representation of the 6-DoF BlueROV2 vehicle uses USBL positioning data to drive the movement of its virtual body [20]. Cross-platform visualization nevertheless remains constrained by the computational requirements

of dynamic rendering in the marine environment. Likewise, although LiDAR–AIS fusion improves multi-target tracking for autonomous surface vessels (ASVs) [29], the workflow relies on Kalman filtering to compensate for signal loss.

Finally, module (v) is tightly coupled with module (iii) through interfaces that coordinate simulation, visualization, and physical–virtual state exchange. In a marine implementation, a hybrid test system for USVs achieved real-time pose synchronization between the physical vessel and its virtual representation through spatial registration [30]. Nevertheless, physical–virtual registration remains sensitive to ocean disturbances; for instance, surge and heave motion can introduce displacement errors that expose limitations in inertial compensation. At the human–machine interaction layer, the semi-autonomous ROV infrastructure integrates predictive guidance and visualization [20], but communication delay can still produce lagged visual or control feedback during close-range operations.

Accordingly, CFD, multibody solvers, POD reduced-order models, game engine environments, learned surrogates, and communication middleware are treated as DT-enabling components unless the reported workflow connects them to a physical asset.

3.2. Multiphysics Modeling and Simulation

The DT platform's core capability lies in providing a high-fidelity virtual environment to simulate multiphysics field coupling between marine robotics and complex ocean environments, such as flow and wave fields. The accuracy of marine robotics DTs critically depends on effective modeling of interactions between the rigid body, fluid, and structure; however, uncertainties in ocean dynamics and sensor limitations make it difficult to maintain both physical fidelity and real-time responsiveness, necessitating joint advances in computational mechanics, environmental reconstruction, and data assimilation.

Within this context, multibody dynamics frameworks such as ADAMS provide detailed motion predictions for underwater gliders by simulating buoyancy–propulsion interactions [31], while RecurDyn–AMESim co-simulation architectures capture the coupled behavior of mechanical structures and hydraulic controllers for seabed ROVs [32]. Computational fluid dynamics (CFD) further enriches these models, as demonstrated in hybrid autonomous underwater vehicles (HAUV), where elevator-induced pitching has been validated using Ansys Fluent simulations [33]. Still, high-fidelity hydrodynamics models suffer from poor scalability in turbulent flows, prompting the use of evolutionary algorithms to identify effective hydrodynamic coefficients in transient regimes as a pragmatic compromise between accuracy and computational load [13].

To better reconstruct environmental boundary conditions, researchers have developed virtual seabed terrain models using marine survey data from the Jeju Sea and validated real-time tracking accuracy against multibody dynamics models [14]. At the guidance level, integral line-of-sight (ILOS) control mitigates ocean current drift in underactuated vehicles by embedding integral actions into the guidance law [34]. However, both terrain reconstruction and ILOS-based control show fragility under sparse or noisy sensing, highlighting the need for physics-informed digital twins that can infill missing information. Representative examples include ZodiAq's Cosserat-rod-based model, which captures isotropic flagellar propulsion in unstructured flow environments [15], though at the cost of increased model and implementation complexity.

Building on these foundations, modular co-simulation in game engine-like environments has been explored to accelerate marine data generation. The integration of Gazebo with DAVE project plugins, for instance, enables efficient synthesis of front-looking sonar scenes and acoustic datasets [35]. While such environments can shorten dataset development, their role as DT components depends on whether simulated outputs are linked to physical measurements and validated for the intended marine platform. Their computa-

tional benefits also remain contingent on access to representative high-resolution datasets and suitable accelerator hardware, which are not always available in field deployments.

Soft marine robots require compliant multiphysics models that represent large structural deformations and fluid–structure interaction. The ZodiAq underwater drone, for example, uses Cosserat-rod formulations to couple deformable structures with surrounding flows [15]. Such models can improve physical representation, but their computational cost conflicts with the latency and power constraints of onboard processing. Reduced-order models, learned surrogates, and hardware acceleration are being investigated, although their performance on physical marine platforms remains incompletely validated.

4. Typical Applications

Building on the generic architecture and key functional modules discussed in Section 3, this section examines DT-related models and workflows reported across representative marine robotic platforms. We organize the review by platform type, focusing on AUVs, ROVs, USVs, and emerging marine robotic platforms. The term “DT-related” is used as an umbrella description; the evidence class of each audited study depends on its reported physical–virtual data flow, update mode, and validation setting, as summarized in Table 2.

4.1. Applications of AUVs

For AUVs, DT-related workflows are used to develop and validate control strategies in virtual environments. Their practical use depends on balancing model fidelity, computational cost, and adaptation to variable ocean conditions.

To mitigate this challenge, physics-informed reinforcement learning (RL) frameworks embed hydrodynamic priors directly into the learning architecture, enabling zero-shot transfer from virtual to physical platforms without requiring extensive fine-tuning while at sea. The PICOPO algorithm [12] constructs a physics-informed virtual dynamics model from 2000 data samples and uses the model for controller development and one-time sim-to-real transfer. Under the adopted classification, this workflow is treated as a digital model/virtual prototype because the reported process does not maintain automated bidirectional synchronization after controller transfer. The study reports sample efficiency and transfer across the evaluated docking and trajectory-tracking tasks. However, its reliance on simplified Navier–Stokes approximations introduces divergence risks in turbulent flows, which become more pronounced when scaling to multi-vehicle systems where mutual hydrodynamic interference exacerbates model uncertainty.

Building on single-vehicle control, DT-related virtual environments have also been used to develop coordinated AUV behaviors. Edge computing-based platforms couple distributed learning with in situ sensing, but face inherent trade-offs between communication latency and swarm intelligence. Yang et al. [36] mapped real ocean dynamics into a sensor-fed virtual environment, allowing RL controllers to optimize formation paths with respect to ambient currents. Wen et al. [16] further developed an enhanced artificial potential field method for behavior-based path optimization, enabling multiple AUVs to execute task plans under a leader–follower architecture. Their formation controller for networked AUVs combines a marine communication model with an AUV physics engine in a simulation-only virtual environment. Because the reported states are generated within Gazebo and no physical AUG data stream is connected to the evaluated loop, this workflow is classified as a digital model/virtual prototype rather than a bidirectional DT [16]. Nonetheless, these systems expose new trade-offs: Du et al.’s data-driven state predictor [37] effectively compensates for communication delays in 3D formations, but at the cost of increased energy consumption, whereas Zhou et al.’s event-triggered

strategy [38] alleviates network congestion but degrades tracking accuracy during highly dynamic maneuvers.

Beyond control, AUV-oriented DT-related simulations and enabling methods have been investigated for perception tasks such as leak detection and object manipulation. Hu et al. [39] evaluated Faster R-CNN and YOLOv4-Tiny for gas leak plume detection on a Jetson Nano-equipped robotic fish. The benchmark comprised 8622 annotated images collected from three 120-s physical underwater gas leak experiments conducted at pressures of 0.2, 0.4, and 0.6 MPa. The inference time comparison reported 71 ms per image for YOLOv4-Tiny and 3057 ms for Faster R-CNN, corresponding to a 43-fold difference. This source-specific comparison concerns detector inference on the reported hardware and experimental dataset; therefore, it is treated as DT-enabling perception evidence rather than as a 43-fold improvement in end-to-end DT-system performance. Chu et al. [40] improved the navigation of underactuated AUVs in cluttered debris fields via DDQN-based path planners trained entirely in digital twin environments, supporting obstacle avoidance in the reported moderate-current simulations. Despite these gains, performance deteriorates in turbid waters or in the presence of strong vortices, underscoring a persistent dependence on high-fidelity environmental models that are costly to run in real time on embedded hardware.

Across the reviewed AUV studies, higher model fidelity increases computational demand, while distributed control remains constrained by communication latency and energy availability. These limitations motivate adaptive fidelity models and communication-aware validation.

4.2. Applications of ROVs

For ROVs, digital twin development must balance modeling granularity against the cost and reliability constraints of complex subsea operations. Rather than uniformly digitizing all components, recent work advocates a triage-based strategy that prioritizes critical subsystems.

Representative studies [22] show that focusing the digital twin on key subsystems such as thrusters and sensor suites can substantially reduce computational demands while improving overall mission reliability, an important advantage given the bandwidth and processing limitations of deep-water deployments. However, this selective modeling strategy inevitably sacrifices system-wide observability, risking undetected degradation in non-prioritized subsystems over long-duration missions and exposing a trade-off between computational efficiency and diagnostic completeness.

Advances in subsystem-level modeling have also enabled digital shadow-style operator support through multimodal feedback. Beyond conventional video feeds, line-of-sight guidance systems [20] convert path-tracking objectives into heading commands via dynamically updated waypoints, maintaining precise trajectories under turbulent conditions. This guidance is complemented by hydrodynamic data-driven virtual reality environments [19] that reconstruct microscale flow dynamics to anticipate collision risks, providing operators with an immersive understanding of the proximity between tools, structures, and the surrounding flow. Under the adopted classification, the workflows reported in [19,20] are treated as digital shadow concepts since physical or environmental data update the virtual or operator-facing representation, while an automated DT-generated V→P decision or control return path is not demonstrated.

At a higher level of organization, digital twins support the shift from single-ROV missions to fleet-level coordination. Shore-based control hubs such as OceanLab [41] federate heterogeneous assets through cloud-centric frameworks, enabling experts to collaboratively manage ROV swarms and seabed infrastructure remotely so as to avoid direct human

exposure to hazardous environments. However, this increased connectivity amplifies cybersecurity risks: in multi-tenant environments, spoofed or tampered sensor streams can propagate through shared digital twin infrastructures, and systematic mitigation strategies are still underexplored.

Zhang et al. [42] reported a DT-driven ROV formation control prototype in which periodically returned physical states update the virtual model and a control policy generated in the virtual model is applied to the ROVs. Under the adopted criteria, this workflow is treated as a bidirectional DT prototype rather than an operational DT, as repeated or sustained deployment is not reported. The study reports improved formation performance and reduced communication energy within its experimental setting.

Marine infrastructure modeling provides contextual evidence for how ROV observations can be incorporated into asset-level integrity workflows. Corrêa et al. [43] developed a retroanalysis procedure that uses geometric data collected during ROV surveys to update and calibrate numerical models of the mooring lines and risers of floating production systems. Because the twinned asset is the floating production system rather than the ROV, this study is treated here as contextual evidence for ROV-enabled data acquisition and model updating rather than evidence of a robot-centered operational DT. Nevertheless, the workflow illustrates a practical interface between robotic inspection and marine asset models; extending it to a robot-centered DT would require automated and traceable data exchange, physical–virtual synchronization, and validation under intermittent underwater communication.

4.3. Applications of USVs

For USVs, digital twins primarily serve to fuse heterogeneous sensor streams into cohesive virtual representations of the maritime environment and to validate advanced control and coordination schemes. This fusion makes explicit a central trade-off between real-time responsiveness and model fidelity.

On the perception side, LiDAR–AIS fusion frameworks (Figure 7) demonstrate high multi-target tracking accuracy in dense traffic by clustering LiDAR point clouds, fitting NSDLS ellipses to target extents, and applying Kalman filtering for state prediction [29]. Vision-based systems such as the LKEDN-MHP network [44] further enhance situational awareness by improving dehazing performance in the reported evaluation via large-kernel encoder–decoder architectures. Both approaches are computationally intensive; high-resolution LiDAR severely taxes onboard processors during peak-traffic periods, while deep dehazing networks add latency. An ASV prediction study illustrates the effect of delayed sensor updating: when the update interval was extended in the reported test configuration, the mean absolute error for yaw increased from 18.754° to 26.289° , corresponding to a 40.18% increase, while the same error for distance increased from 1.411 m to 2.670 m, an increase of 89.23% [45]. Still, these results describe one controlled experimental configuration and should not be interpreted as a universal update interval threshold.

Multi-USV scenarios use DT-related simulation, communication, and synchronization workflows to evaluate distributed control architectures that must simultaneously maintain formation accuracy and communication resilience. Dynamic time assignment mechanisms (DTACM) [46] mitigate channel congestion through interleaved group communication, but Monte Carlo analyses indicate that this regular structure opens up attack surfaces for organized denial-of-service (DoS) assaults, potentially destabilizing formations under adversarial traffic patterns [47]. To counter this, intermittent anti-competition protocols (IDIPETM) [48] introduce exclusive interleave biases that lower overall throughput while preserving formation integrity during communication blackouts. However, these schemes, together with hierarchical

swarm controllers [21] that require dual-layer synchronization between physical and virtual swarms, lead to increased controller design complexity. Among these examples, Yu et al. [21] provided evidence of an online bidirectional DT prototype through physical–virtual state and control exchange. The remaining communication and control methods are treated as DT-enabling evidence unless an integrated physical–virtual return path is reported.

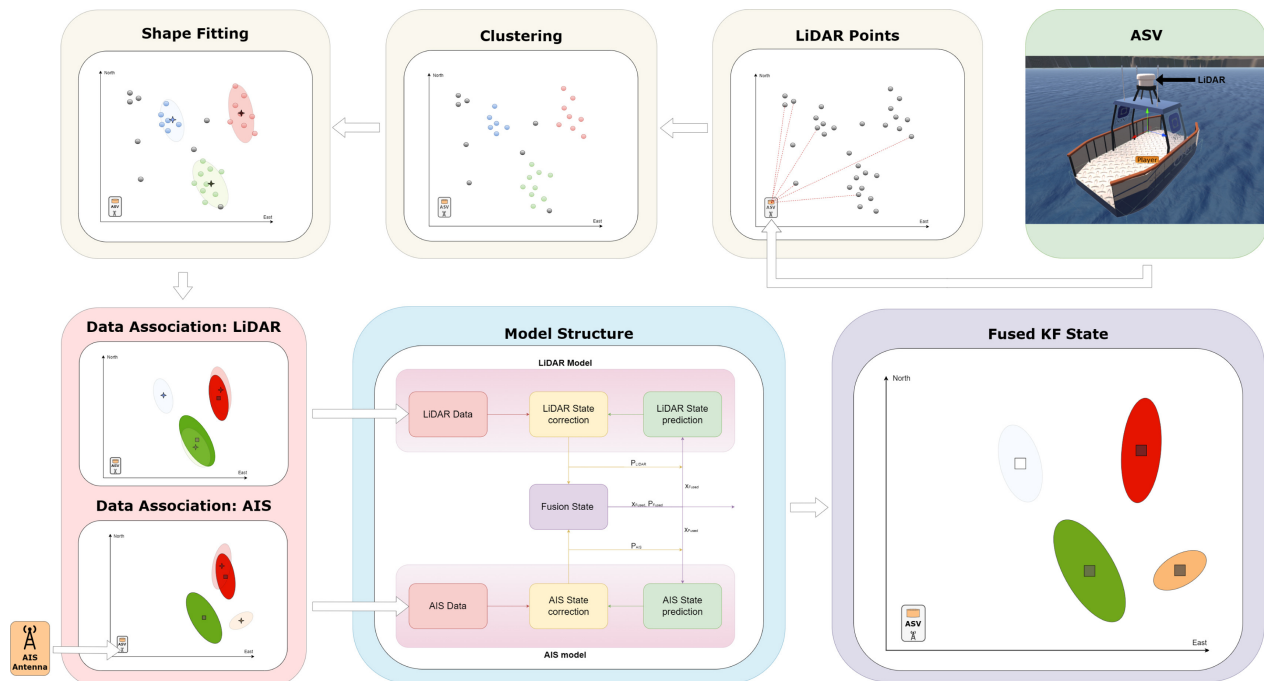


Figure 7. Overview of the LiDAR–AIS multi-target tracking workflow, including LiDAR point cloud preprocessing, shape fitting, LiDAR and AIS data association, Kalman filter state fusion, and the resulting target tracks. Reproduced from Figure 6 of [29].

Regarding validation, hybrid virtual–real workflows provide controlled settings for evaluating marine robotic control and perception before field deployment. Twin-driven HIL platforms have been used to validate visual servo controllers under repeatable test conditions [49]. Such evaluations nevertheless remain bounded by the environmental effects represented in the test system; factors such as biofouling-induced drag, sensor degradation, and long-term hydrodynamic variation are rarely reproduced, limiting the ability to predict sustained field performance.

Digital twins also facilitate tighter coordination between USVs and UAVs. In pollution monitoring missions, UAV-based aerial reconnaissance identifies and localizes surface debris, while USV fleets execute collection tasks guided by digital twin-optimized scheduling. Particle swarm-based load balancing strategies [50] reduce overall cleanup time by adaptively distributing tasks according to real-time vehicle states and environmental conditions.

Across the reviewed USV studies, idealized simulation conditions, onboard processing costs, and fragmented resilience evaluation limit evidence for operational maturity. These limitations are considered further in Section 5.

4.4. Applications of Emerging Marine Robotic Platforms

Beyond conventional AUVs, ROVs, and USVs, digital twin technology is also reshaping emerging classes of marine robots, including underwater gliders, bioinspired soft robots, and self-reconfigurable systems. These platforms pose distinct modeling and control challenges that further stress the limits of current multiphysics and real-time data fusion techniques.

Underwater glider studies use DT-related virtual models and monitoring workflows for kinematic simulation and structural health assessment. By combining strain-sensor layout optimization with attitude-driven strength assessment, these workflows can support evaluation of structural safety during launch and recovery [51,52]. Their evidence class depends on whether the reported physical measurements update the virtual representation automatically and whether an automated return path is implemented. Virtual prototyping pipelines increasingly replace physical trials, using multi-fidelity simulations to optimize control strategies and buoyancy regulation while maintaining kinematic accuracy comparable to sea trials [31]. However, such high-fidelity models are computationally demanding: repeated calibration of numerical models against experimental data introduces latency, and mapping sparse sensor measurements to full-field strain via Isomap-RBF surrogates [51] further complicates deployment on resource-constrained platforms. Industrial frameworks such as Petrel's digital twin platform respond by emphasizing scalable lifecycle management that couples rapid design iteration with operational uncertainty quantification [53]. However, their effectiveness is often curtailed by interdisciplinary data silos and incompatibilities among heterogeneous simulation tools.

In soft marine robotics, digital twins are leveraged to capture complex fluid–structure interactions arising from compliant biomimetic designs. The ZodiAq soft underwater drone uses a Cosserat rod-based virtual model to represent coupled flow–structure dynamics [15]. The model and physical prototype were evaluated separately, and automated online physical–virtual exchange was not reported; therefore, the study is classified as a digital model/virtual prototype rather than a bidirectional DT. A related physical prototype study developed a hydraulically controlled soft dock for dynamic AUV recovery [54]. The dock completed 18 successful recoveries in 20 dynamic tests, corresponding to a 90% success rate, with a maximum tested AUV velocity of 1.6 m/s. This result characterizes the docking hardware and hydraulic control prototype rather than the performance of an operational DT; nonetheless, it provides a physical validation target for future twin-assisted docking studies. However, the same compliance that enables safe interaction with marine life introduces pronounced hyperelastic nonlinearities and strong hydrodynamic coupling, which complicate real-time prediction and control.

Self-reconfigurable robotic systems further extend the design space by introducing modular morphologies. Here, virtual models serve as low-cost testbeds for evaluating locomotion strategies and reconfiguration policies. By simulating the dynamics of modular robots across hierarchical module–topology–configuration spaces, researchers can assess gait efficiency and fault recovery behaviors without extensive physical experimentation [55]. These studies use virtual models to evaluate locomotion and reconfiguration policies before physical testing, but do not by themselves establish operational DT deployment. For emerging platforms, applicability remains constrained by nonlinear mechanics, uncertain sensing, and limited evidence for real-time physical–virtual coupling.

To improve the readability of the cross-platform comparison, the synthesis is presented in two complementary tables. Table 3 summarizes the reported data sources, model bases, and communication or update modes of the 11 full-text audited cases, while Table 4 summarizes their lifecycle functions, validation settings, evidence classes, and principal limitations. Because the audited studies do not report model fidelity using a common quantitative metric, model characteristics are represented by the implemented model basis and validation context.

Table 3. Technical characteristics of the five platform groups represented in the 11 full-text audited cases, covering reported data sources, model bases, and physical–virtual communication or update modes.

Platform	Reported Data Sources	Model Basis	Communication or Update Mode
AUV/UUV	Experimentally derived system metrics, velocity and control data, and trial trajectories [12,13,22]	Real-UUV system models, physics-informed dynamics models, and calibrated 6-DOF hydrodynamic models	Offline or iterative physical-to-virtual calibration and one-time controller transfer; a continuing automated physical–virtual link was NR
ROV	USBL position, vehicle attitude, and environmental or spatial sensor data [19,20]	Dynamic vehicle and Unity models; Gazebo–Unity virtual-workspace models	Online physical-to-virtual updating through tether, USBL, ROS, or operator-facing visual and haptic interfaces; an automated DT-generated return command was NR
USV/ASV	GNSS, control, vessel-state, and formation-state data; one audited case used simulated vessel states [17,18,21]	Graphical vessel and adaptive-EKF models, NMPC and DRL models, and Unity3D vessel and environmental models	Physical-to-virtual estimation and visualization, virtual-only closed-loop updating, and online physical–virtual state/control exchange via TCP/IP or serial links were reported across the three cases
Underwater glider/AUG	Attitude and position states generated in Gazebo; no physical AUG data stream was reported [16]	Formation-control, path-planning, vehicle, and ocean-current models	Virtual-only Gazebo–ROS–WebGL exchange; physical updating was NR
Emerging soft/tracked	Terrain-contact test data, depth and IMU feedback, and actuator commands [14,15]	Real-time terrain-contact and multibody-dynamics models; Cosserat-rod models of compliant structures	Offline component validation or local robot feedback; automated remote physical–virtual synchronization was NR

Table 4. Evidence and deployment characteristics of the five platform groups represented in the 11 full-text audited cases, covering lifecycle functions, validation settings, evidence classes, and principal limitations.

Platform	Lifecycle and DT Functions	Validation Setting and Evidence Class	Operational Maturity and Principal Limitation
AUV/UUV	Design and development; virtual testing and verification; mission operation and control; M1, M2, and M4	Analytical, simulation, and laboratory evaluations; one DT-enabling method/component and two digital models or virtual prototypes	Sustained synchronization and operational deployment were NR; online coupling under uncertain marine conditions remains limited (C1–C3)
ROV	Mission operation and control; training and human interaction; M3–M5	Laboratory/HIL and field/port prototypes; both audited ROV cases exhibited digital-shadow patterns	An automated DT-generated virtual-to-physical return path and sustained deployment were not established in the two audited cases (C2–C4)
USV/ASV	Virtual testing and verification; mission operation and control; monitoring and diagnosis; M1–M5	Simulation, field/sea-trial digital-shadow evaluation, and a field-validated bidirectional DT prototype	No audited case demonstrated repeated operational deployment; sustained use, drift management, and interoperability remained NR (C1, C3, C4)
Underwater glider/AUG	Virtual testing and mission planning; M2, M4, and M5	Simulation-only evaluation; digital model or virtual prototype	No audited physical–virtual prototype was identified; physical synchronization, operational coupling, and interface reuse remained open (C1–C4)
Emerging soft/tracked	Design and development; virtual testing and verification; control; M1, M2, and M4	Component and laboratory evaluations; one DT-enabling method/component and one digital model or virtual prototype	No integrated field DT was reported; real-time multiphysics computation and online physical–virtual updating remain limited (C1, C2, C4)

Within the 11 cases subjected to full-text auditing, the evidence classes varied across the five represented platform groups. The audited USV/ASV cases included one field-validated bidirectional prototype, whereas the two audited ROV cases exhibited physical-to-virtual monitoring and operator-facing digital shadow patterns. The audited AUV/UUV cases emphasized enabling methods, calibrated virtual models, and sim-to-real transfer without sustained online synchronization. The single underwater glider case remained simulation-based, while the two emerging-platform cases reported component or laboratory validation without an integrated bidirectional DT. No audited case documented repeated operational deployment. These observations apply only to the purposively selected case set.

5. Main Challenges

Building on the enabling technologies reviewed in Section 3 and the platform-specific evidence in Section 4, we derive four cross-cutting challenges by comparing the reported limitations across the retained studies. Representative links between the individual studies, technical characteristics, evidence classes, validation settings, and platform-level gaps are provided in Tables 2–4. The resulting challenges are: (i) the trade-off between modeling accuracy and computational efficiency across multiphysics modules and control loops; (ii) the representation of marine environmental complexity and uncertainty in coupled field models; (iii) synchronization and communication constraints in latency-prone physical–virtual loops; and (iv) integration and standardization gaps across platforms, tools, and lifecycle stages. These challenges correspond to the C1–C4 structure summarized in Figure 8.

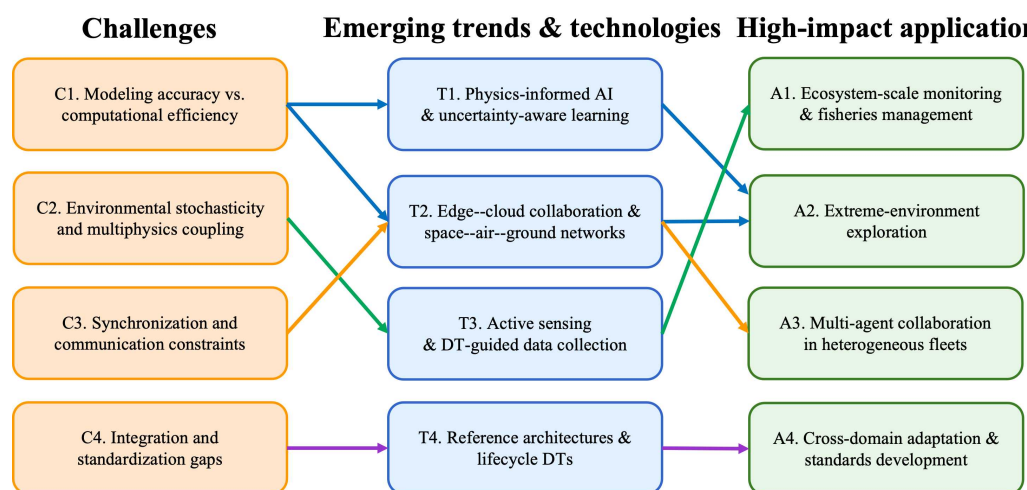


Figure 8. Synthesis linking four cross-cutting challenges in marine robotics DTs (C1–C4) with corresponding research directions and enabling technologies (T1–T4) and representative application frontiers (A1–A4). Source: authors' synthesis.

5.1. Challenge 1: Modeling Accuracy and Computational Efficiency

The growing demand for immediate interaction in marine robotics DTs forces a persistent trade-off between modeling accuracy and computational efficiency, a tension that is particularly acute in the multiphysics modules of Section 3.2 and the real-time control scenarios in Section 4. While high-fidelity simulations can capture critical hydrodynamic and structural dynamics, their substantial computational cost undermines the role of digital twins as real-time decision-making tools. This compromise is most evident in tasks such as underwater manipulation, where delays in predicting stress fields [56] or in thruster control loops [57] can trigger cascading failures.

To operate within real-time constraints, three interrelated approaches have emerged, each proposing a different compromise between physical fidelity and computational load.

Model simplification for constrained hardware. A first line of work explicitly sacrifices some physical detail to achieve operational feasibility. For underwater tracked vehicles on uneven seabeds, replacing fully coupled multibody dynamics (MBD) with triangular patch contact calculations improves both the accuracy and speed of contact resolution, enabling on-the-fly trajectory adjustments without specialized accelerators [14]. In seabed ROVs, RecurDyn/AMESim co-simulation decouples mechanical dynamics from hydraulic control loops, preserving key transient behaviors while meeting real-time constraints [32]. More aggressive gains are achieved through techniques for reducing mathematical order. In AUV support platforms (Figure 9), Proper Orthogonal Decomposition (POD) compresses large finite element models by extracting eigenvectors that dominate structural energy, sharply reducing the cost of computing deformation fields across sea states [58]. How-

ever, these reduced models are context-sensitive; this means that equations calibrated under nominal conditions can break down in the presence of unmodeled phenomena such as vortex-induced vibrations, underscoring the risk of over-reliance on fixed operational envelopes.

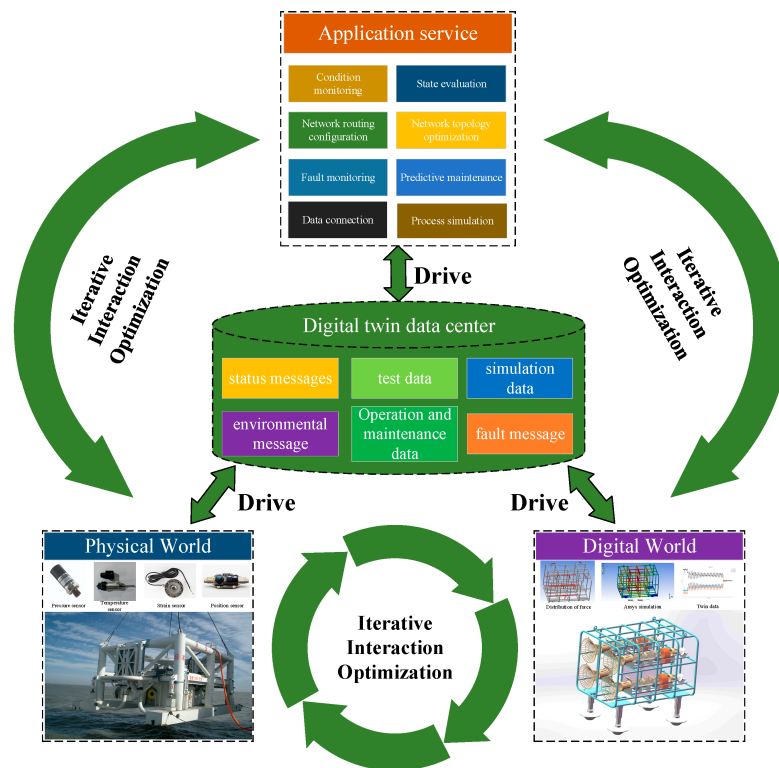


Figure 9. Five-dimensional DT architecture of an AUV underwater support platform, linking the physical world, digital world, twin data center, application services, and data connections. Reproduced from Figure 1 of [58].

Machine learning surrogates in the simulation pipeline. A second line of work uses data-driven or physics-informed surrogate models to reduce dependence on repeated high-fidelity simulation. For AUV motion control, PICOPO constructs a physics-informed dynamics model from a limited offline dataset and uses it as a DT environment for offline policy training [12]. This marine example indicates that learned models can reduce the need for real-world interaction during controller development, but does not establish a general computational speedup across platforms; its transferability remains constrained by the coverage of the training data and by the adequacy of the embedded hydrodynamic assumptions under previously unobserved operating conditions.

Virtual prototyping as a validation bridge. A third strand uses virtual prototyping to compare model predictions with physical measurements before an integrated DT workflow is deployed. For blended wing-body underwater gliders, a laboratory demonstrator links attitude measurements to structural field prediction and virtual visualization [52]. For tracked underwater robots, a real-time terrain contact solver has been evaluated against multibody dynamics references and controlled test data [14]. While these studies improve confidence in individual models and components, they remain laboratory- or component-level validation; neither establishes sustained online physical–virtual synchronization in an operational marine mission.

Across these approaches, differences in tasks, hardware, fidelity measures, and latency reporting prevent direct comparison. Shared benchmarks that report both prediction error and computational cost are needed for representative marine tasks.

5.2. Challenge 2: Modeling Marine Environmental Complexity

A second cross-cutting challenge concerns the representation of marine environmental complexity and uncertainty within coupled field models, directly affecting the predictive reliability of the digital twins introduced in Section 3.2 and their application in Section 4. The fidelity of physical field coupling is foundational for environmental modeling, yet the strong spatiotemporal heterogeneity of ocean processes introduces substantial uncertainty at coupling interfaces. This dual difficulty not only degrades robotic motion control (for example, increased USV attitude prediction errors in wave environments [59]) but undermines disaster warning functions, as is the case in gas leakage plume dispersion models that must satisfy strict accuracy requirements for early detection [39].

Cross-scale multiphysics coupling. The complexity of multiphysics coupling is salient in cross-scale interaction mechanisms. In ROV operations [19], fluid–structure coupling requires real-time turbulence measurements via distributed sensors and digital twins to provide tactile feedback. However, the mesh resolution needed for macroscopic flow simulations complicates accurate estimation of instantaneous impact forces on manipulator links. Even more challenging is the coupling between current and kinematics in USVs [60,61]; when traversing spatially and temporally varying currents, conventional path planners often neglect the dynamic interplay between fluid momentum transfer and hull inertia, leading to systematic discrepancies between predicted and realized trajectories.

Uncertainty quantification and swarm decision-making. Efforts to quantify environmental uncertainty increasingly combine stochastic filtering with swarm intelligence algorithms, but balancing robustness and computational cost remains difficult. An enhanced unscented Kalman filter (UKF) [59] with dynamic sliding windows can update USV motion states in real time under wave disturbances, effectively reducing attitude prediction errors at the price of elevated computational load. In multi-AUV collaborative sampling [62], mutual information-based path planning suffers from rapidly growing computation time as Gaussian process regression adds new observation points. For multi-USV systems, the MSCMO framework [63] decomposes temporal and collision probability constraints to improve task completion rates under current disturbances, yet its performance hinges on the same trade-off between model richness and tractability. Across these examples, multi-source data fusion amplifies environmental model uncertainty rather than attenuating it, linking this challenge directly to the synchronization and communication issues explored in Section 5.3.

Extreme environments and closed-loop validation. Modeling extreme environments further exposes the need for closed-loop digital twin verification. Fluid–chemical coupling models of methane seep regions [39] must incorporate in situ mass spectrometry in order to refine turbulent diffusion coefficients; however, current ROV sensor arrays cannot simultaneously capture detailed velocity fields and gas concentration gradients, leaving critical gaps in model calibration. This limitation marks an important frontier for the next generation of environmental digital twins.

The reviewed studies indicate that uncertainty at field-coupling interfaces remains difficult to quantify. Future marine DT evaluations should report how heterogeneous sensor data, latency, and model uncertainty affect prediction and control performance.

5.3. Challenge 3: Synchronization and Communication Constraints

The third challenge concerns maintaining trustworthy synchronization between physical robots, environmental states, and virtual models under marine communication constraints. Unlike terrestrial robotic systems, marine platforms often depend on acoustic, intermittent, or relay-based links with bandwidth and latency that vary with depth, sea state, vehicle motion, and network topology. This limitation directly affects DT usefulness,

since if the virtual model is updated too slowly it may become a misleading decision aid rather than an operational asset. For USVs, digital twin prediction studies show that longer update intervals can substantially increase yaw prediction errors [45]. For ROV teleoperation, lagged tactile feedback and delayed visual cues can reduce operator confidence and increase the risk of erroneous maneuvers during close-range intervention tasks [19,20].

Latency-aware synchronization. Current synchronization strategies rely on a mixture of state prediction, event-triggered communication, and edge-side filtering. Data-driven state predictors compensate for delays in multi-AUV formations, but this improvement can increase computation and energy consumption [37]. Event-triggered mechanisms reduce unnecessary transmissions in networked AUV and USV systems [38,64], yet aggressive traffic reduction can degrade tracking accuracy during high-dynamic maneuvers. These studies indicate that synchronization must be treated as a joint control, communication, and data assimilation problem rather than purely as a networking issue.

Cybersecurity and data trust. The same connectivity that enables fleet-level DTs also expands the attack surface. In multi-USV formations, denial-of-service attacks and adversarial channel congestion can destabilize coordinated behaviors [46,47]. For cloud-centric ROV or multi-tenant DT infrastructures, spoofed or tampered sensor streams can propagate through shared models, corrupting both situational awareness and downstream control decisions. Their computational overhead, governance requirements, and integration burden remain significant for marine platforms with limited power and intermittent communication. Overall, synchronization and communication constraints determine whether marine DTs can move beyond retrospective monitoring towards real-time decision support.

5.4. Challenge 4: Integration and Standardization Gaps

The fourth challenge is the absence of widely accepted reference architectures, interfaces, and evaluation benchmarks for marine robotics DTs. Existing systems often combine bespoke hydrodynamic solvers, robot middleware, environmental models, visualization engines, and cloud or edge services. This heterogeneity encourages rapid prototyping but also limits transferability, as DT components developed for a specific AUV, ROV, USV, or glider become difficult to reuse across platforms, missions, and vendors.

Toolchain fragmentation. Representative studies already show partial solutions. FMI-based component models in the CARES architecture support modular co-simulation [65], while NAVIDRO-style interfaces improve collaborative simulation configuration for underwater vehicles [20]. Industrial lifecycle frameworks for underwater gliders further demonstrate how parametric design, multiphysics simulation, and in-service monitoring can be linked within a DT workflow [53]. Nevertheless, these solutions remain fragmented. Model fidelity, data schemas, time synchronization, uncertainty representation, and visualization conventions are rarely standardized, making it difficult to compare performance across studies or to reproduce DT behavior outside the original implementation context.

Benchmarking and lifecycle governance. Standardization gaps also affect evaluation. Many studies report local improvements in control accuracy, simulation speed, perception quality, or energy consumption, but few benchmark these gains against common marine tasks with shared latency, fidelity, and robustness metrics. This limits the ability to judge whether a method is generally useful or merely tuned to a narrow scenario. Another open issue is lifecycle governance; as DTs evolve from design-stage simulation to operation-stage monitoring and maintenance, authors must specify how models are updated, validated, archived, and audited over time.

Closing this gap requires community-level reference architectures for AUV, ROV, USV, and hybrid sea–air systems together with open benchmark suites that jointly evaluate physical fidelity, latency, data quality, cybersecurity, and operational robustness. Without

such standards, marine robotics DTs will likely remain powerful but isolated prototypes rather than interoperable engineering infrastructures.

6. Future Trends and Outlook

6.1. Convergence of Artificial Intelligence

In response to the challenges of modeling accuracy, data efficiency, synchronization, and standardization highlighted in Section 5, artificial intelligence is being investigated as a means of developing physics-informed and uncertainty-aware marine robotics DTs. This evolution calls for a careful examination of how machine intelligence reshapes predictive accuracy while introducing new forms of epistemic and ontological uncertainty.

This trend is particularly evident in reinforcement learning (RL) frameworks, where physics-informed neural networks aim to overcome limitations of conventional simulation. For instance, Li et al.'s PICOPO framework achieves zero-shot sim-to-real transfer for AUVs by embedding hydrodynamic principles directly into the learning architecture [12]. By constructing a physics-informed digital twin from only a few thousand samples, PICOPO improves long-horizon motion prediction and reduces the need for risky in situ exploration. However, the method's performance is tightly coupled to the adequacy of first-principle embeddings; simplified Navier–Stokes approximations can break down in unmodeled turbulent regimes, echoing the vulnerability of reduced-order models discussed in Section 5.1 [12].

At the fleet level, digital twin-enabled RL is increasingly used to coordinate multiple agents under dynamic marine conditions, addressing part of the environmental complexity challenge in Section 5.2. Yang et al. combine value-based RL with edge computing so that AUGs can adapt their path planning online to changing ocean currents [36]. This improves responsiveness but also drives up computational demand, which grows nonlinearly with environmental variability, potentially eroding real-time guarantees during extreme events [36]. In multi-USV systems, Zhang et al.'s value decomposition network partitions task allocation and collision avoidance into specialized learning modules, reducing the effective exploration dimensionality [66]. However, this decomposition relies on region-partitioning heuristics that may suppress emergent cooperative behaviors beyond predefined operational boundaries [66].

Taken together, these AI convergence paths illustrate a recurring pattern: gains in predictive performance, sample efficiency, or autonomy come at the cost of new uncertainties in physical fidelity, multi-agent coordination, and sim-to-real robustness. Future research needs to integrate physics-informed RL, systematic uncertainty quantification, and verification tooling into marine DT workflows so that AI-enhanced digital twins can support safe autonomy and reliable decision-making in sustainable ocean operations.

6.2. Edge Computing and Prospective 5G/6G Integration

Marine robotic digital twins must reconcile latency-sensitive onboard tasks with limited computing resources and intermittent communication links. Edge computing provides a practical mechanism for partitioning these workloads. Navigation, state estimation, event filtering, and short-horizon control can be executed near the physical platform, whereas computationally intensive model training, long-horizon simulation, and fleet-level data management can be assigned to surface gateways or cloud servers. This partitioning is particularly relevant to marine systems in which underwater acoustic links connect submerged vehicles to surface nodes while radio, cellular, or satellite links connect those nodes to shore-based infrastructure.

Direct marine studies provide initial evidence for this architecture. Edge-assisted digital twin environments have been used to support reinforcement learning-based path

planning for underwater vehicles operating under dynamic environmental conditions [36]. Related work combines digital twins with edge computing for formation control for multiple underwater gliders, allowing model updates and coordination tasks to be distributed across networked platforms [16]. At the network level, federated learning-assisted marine digital twin frameworks have been investigated to balance model aggregation, communication security, and energy consumption [67]. Heterogeneous UAV-USV-UUV architectures further illustrate how aerial and surface platforms can act as communication and computing relays for underwater missions [68]. Together, these studies indicate that edge resources can support selected perception, planning, and coordination functions without requiring every computation to be transmitted to a centralized cloud.

However, the reviewed evidence does not yet establish routine operation of 5G/6G-enabled digital twins in realistic marine missions. Most reported architectures rely on simulation, prototype-level validation, or communication assumptions that do not fully represent underwater acoustic bandwidth, variable propagation delay, intermittent connectivity, and the energy constraints of submerged vehicles. Therefore, the role of 5G/6G should be framed as prospective: these networks may support high-capacity links among surface vehicles, aerial relays, offshore infrastructure, and shore stations, but they do not replace underwater acoustic or optical communication. Future marine architectures will need to coordinate these heterogeneous links and explicitly report end-to-end latency, update frequency, packet loss, energy consumption, and synchronization error.

Studies from adjacent domains can offer potentially transferable mechanisms, but should not be treated as direct marine robotics evidence. RIS-assisted aerial offloading, digital twin-based network slicing, and space-air-ground resource allocation suggest methods for adaptive task partitioning and network management [69–71]. However, these studies were developed for industrial IoT or general communication networks; their applicability to marine robotics remains to be validated under platform-specific communication, power, mobility, and safety constraints.

6.3. Potential Applications

Looking beyond current deployments, future applications of marine robotics DTs will increasingly target ecosystem-scale monitoring, extreme environment exploration, and cross-domain collaboration. These directions are tightly coupled to the environmental modeling, synchronization, and integration challenges in Sections 5.2–5.4, and motivate new requirements for multi-fidelity and multi-platform DT architectures.

At the ecosystem level, digital twins are evolving from single-robot simulators into shared environmental backbones. Combined USV, ROV, and AUV campaigns already support detailed coastal habitat assessments using multimetric indices [72], while projects such as SUSHI DROP employ non-invasive UUVs to map fisheries in support of sustainable exploitation [73]. However, extending these efforts into predictive basin-scale ocean twins remains difficult: limited underwater bandwidth constrains real-time data fusion, and current implementations struggle to assimilate highly dynamic environmental data streams into coherent models [28]. Addressing these gaps will require hierarchical multi-fidelity DTs that can degrade gracefully from fine-grained local models to coarser regional representations as communication and sensing conditions change.

Cross-domain robotic collaboration provides another prospective application context. Heterogeneous UAV-USV-UUV networks, conceptually summarized in Figure 10, exploit complementary mobility domains to support sensing, communication relaying, task planning, and underwater intervention. The 3U framework uses deep RL to jointly optimize trajectories and inter-vehicle connectivity [68], while autonomous waste collection systems combine segmented UAV inspections with coordinated USV swarms to reduce

operational costs in surface-cleaning missions [50]. To manage communication constraints, event-triggered control strategies have been proposed for USV-UAV path tracking [64]. As an analogy from an adjacent domain, the mobility DT architecture in [74] illustrates how critical data streams may be prioritized at the expense of spatial or temporal resolution; however, its applicability to heterogeneous marine fleets remains to be validated under intermittent and bandwidth-limited links. Together, the marine evidence and explicitly labeled transferable mechanisms emphasize the need for reference architectures that encode communication, energy, and data resolution trade-offs.

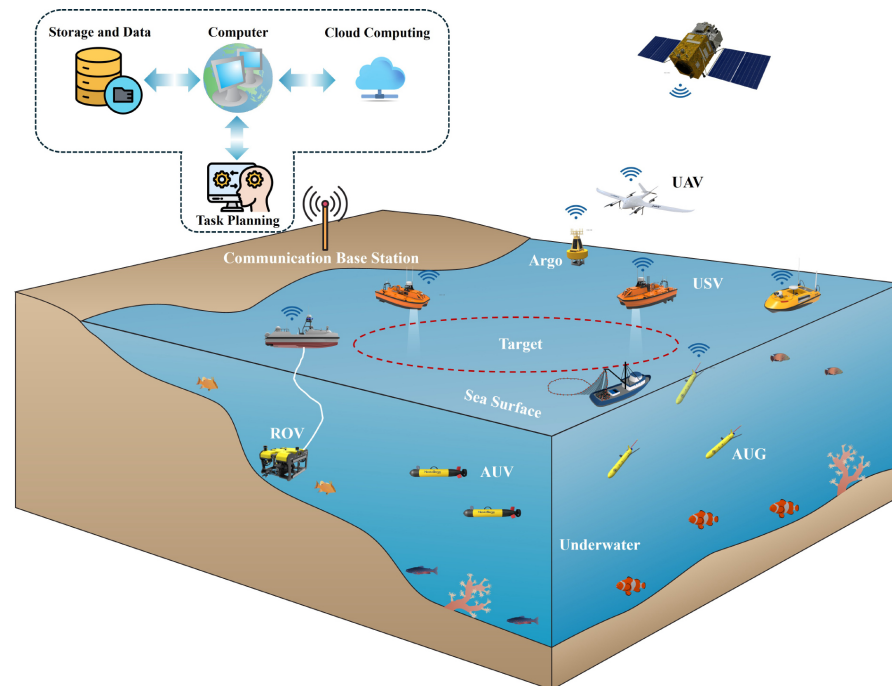


Figure 10. Conceptual schematic of a heterogeneous marine robotics network integrating UAVs, USVs, AUVs or underwater gliders, ROVs, ocean observation platforms, shore or cloud resources, and satellite links. The schematic synthesizes the communication and task planning relationships discussed in this review; the UAV-USV-UUV cooperative target-hunting concept is informed by [68]. Source: authors' schematic.

Finally, while selected cross-domain digital twin studies may inform future marine robotics research, they do not constitute direct evidence for marine robotic DT deployment. For example, vehicle-to-everything communication architectures may suggest candidate mechanisms for message prioritization, link selection, and resource allocation in multi-agent marine systems [75]; however, these mechanisms were developed for ground vehicle networks and require validation under acoustic communication constraints, intermittent connectivity, limited onboard energy, and mission-specific safety requirements. Future work should develop and validate DT reference architectures and interface specifications tailored to AUVs, USVs, ROVs, and underwater gliders. Such architectures should define interoperable data models, synchronization policies, communication interfaces, and validation metrics across platforms and mission stages rather than directly transferring cross-domain designs.

7. Conclusions

This review has examined DT-related work across AUVs, ROVs, USVs, underwater gliders, and emerging marine robotic platforms. The reviewed workflows are used mainly for model construction, simulation, monitoring, control validation, and decision support.

Of the eleven purposively selected cases included in the full-text audit, two were classified as DT-enabling methods or components, five as digital models or virtual prototypes, three as digital shadows, and one as a bidirectional DT prototype. None of these cases documented repeated or sustained operational deployment. Thus, these evidence-class counts and maturity observations are restricted to the audited case set and do not represent corpus-wide estimates of prevalence.

The main deployment constraints are the computational cost of high-fidelity models, uncertainty in marine environmental representation, intermittent communication, data quality and cybersecurity risks, and fragmented interfaces. Future studies should report the data flow direction, update mode, validation setting, and deployment duration; compare methods under shared fidelity and latency metrics; and develop platform-specific interface and evaluation standards. Physics-informed learning, multi-fidelity models, edge computing, and heterogeneous coordination are candidate approaches, but their value requires validation on physical marine platforms.

Progress towards operational marine robotics DTs will also depend on lifecycle governance, maintainable software toolchains, and coordination among researchers, operators, and regulators. On the current evidence, marine robotics DTs should be treated as an emerging engineering approach rather than established foundational infrastructure.

Supplementary Materials: The complete list of literature records reviewed in this study, including detailed bibliographic information, eligibility status, and record-specific exclusion reasons, can be downloaded at: <https://www.mdpi.com/article/10.3390/jmse14151393/s1>.

Author Contributions: Conceptualization, X.W.; methodology, X.W.; software, X.W.; validation, P.W.; formal analysis, L.C. and D.X.; investigation, X.W.; data curation, L.C. and P.W.; writing—original draft preparation, X.W.; writing—review and editing, C.C.; visualization, X.W. and D.X.; supervision, C.C.; project administration, C.C.; funding acquisition, X.W. and C.C. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Natural Science Foundation of China (Nos. 52405287 and 52505033), the Joint Funds of the Natural Science Foundation of Tianjin (No. 25JCLQJC00190), the 2026 Tianjin Metrology Science and Technology Project (No. 2026TJMT053), the Natural Science Foundation of Tianjin (No. 25JCYBJC01650), the Jin'an District Tackle-the-Challenge Project (No. 2025JB06), the National Key R&D Plan of China (No. 2025YFE0214501), and the China Postdoctoral Science Foundation (No. 2025T180377).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: No new empirical data were created in this study. Supplementary Data S1 provides the record-level registry for all 116 Web of Science records, including bibliographic information, eligibility status, and record-specific reasons for exclusion. The underlying bibliographic records remain subject to Web of Science access terms.

Acknowledgments: The authors thank Qing Chang, as the project leader, for supporting this work.

Conflicts of Interest: The authors declare no conflicts of interest; the funders had no role in the design of the study, in the collection, analysis, or interpretation of data, in the writing of the manuscript, or in the decision to publish the results.

Abbreviations

5G	Fifth-Generation Mobile Network
6G	Sixth-Generation Mobile Network
ASV	Autonomous Surface Vessel

AUG	Autonomous Underwater Glider
AUV	Autonomous Underwater Vehicle
DT	Digital Twin
GNC	Guidance, Navigation, and Control
HIL	Hardware-in-the-Loop
IoT	Internet of Things
RL	Reinforcement Learning
ROV	Remotely Operated Vehicle
SHM	Structural Health Monitoring
SIL	Software-in-the-Loop
UAV	Unmanned Aerial Vehicle
USV	Unmanned Surface Vessel
UUV	Unmanned Underwater Vehicle

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