

Review Article

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**Artificial intelligence in offshore wind geotechnical engineering: A
lifecycle-oriented review**

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Abstract. As offshore wind develops toward deeper waters and larger turbine capacities, geotechnical challenges are becoming increasingly complex, involving more variable seabed conditions, larger foundation dimensions, and stricter lifecycle reliability and cost-control requirements. Accordingly, artificial intelligence (AI), with strengths in data fusion, surrogate modeling, and monitoring-informed inference, has increasingly been explored as a complementary computational and analytical tool in offshore wind geotechnical engineering. Particular attention is given to spatially variable ground characterization, surrogate-based response and reliability assessment, and monitoring-informed evaluation of installation and service states. This paper presents a lifecycle-oriented review of AI applications, informed by systematically screened research articles published between 2001 and 2025 and selected project- and industry-level practices. The main AI application pathways are synthesized across site investigation, foundation design, installation, and operation and maintenance (O&M), and are related to stage-specific geotechnical problems rather than algorithm categories alone. The synthesis shows a differentiated maturity pattern across the lifecycle. Foundation design shows the highest research concentration, while project-level digital ground modeling in site investigation and design-stage surrogate analysis show the clearest pathways to engineering use. Closed-loop installation control and below-mudline state inference for O&M remain largely at the research or validation stage. Across these applications, several cross-cutting limitations remain, including sparse offshore data, insufficient physical constraints, limited cross-site generalizability, incomplete standardization, and limited engineering acceptance. Future directions are discussed, including physics-integrated models, high-quality data ecosystems supported by standardized benchmark datasets, certification-oriented validation, and reviewable agent-assisted workflows to support more reliable and cost-effective offshore wind development.

Keywords: offshore wind power; offshore geotechnical engineering; artificial

intelligence; lifecycle

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1 Introduction

Amid the global transition toward low-carbon energy systems ^[1], offshore wind power has expanded rapidly due to its abundant and stable wind resources, high power generation potential, and limited land-use conflicts ^[2,3]. As the industry expands, wind turbine capacities have increased from 2 MW in the early 2000s to 15–20 MW today, pushing wind farm developments into deeper waters and more complex seabed environments ^[4,5] (**Fig. 1**). The Global Wind Energy Council projects approximately 350 GW of new offshore wind capacity worldwide between 2025 and 2034 ^[6]. At the same time, project economics and structural reliability have become increasingly critical. In representative fixed-bottom and floating offshore wind projects assessed by the National Renewable Energy Laboratory, non-turbine infrastructure and operation and maintenance (O&M) contribute 62–65% of the levelized cost of energy (LCOE), while the capital-cost shares of their respective support systems range from approximately 10% to 30% ^[7]. These cost shares highlight the economic importance of non-turbine systems in offshore wind projects. Among these systems, foundations and anchors transfer structural and mooring loads to the seabed, making their performance strongly dependent on ground conditions and soil–structure interaction. Geotechnical engineering therefore plays a central role in both structural safety and economic viability throughout the offshore wind project lifecycle.

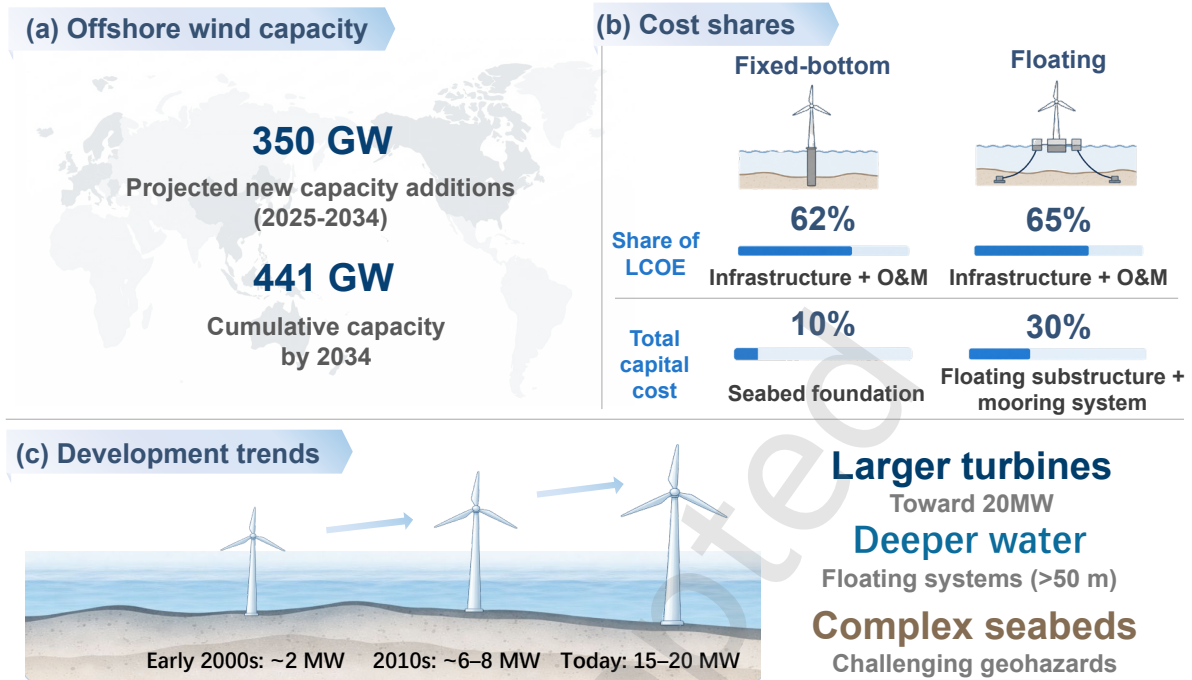


Fig. 1. Key drivers and development trends in offshore wind engineering. (a) Growth in offshore wind capacity [6]. (b) Cost shares for representative fixed-bottom and floating offshore wind projects assessed by the National Renewable Energy Laboratory (NREL) [7]. The upper row shows the share of levelized cost of energy (LCOE) attributable to non-turbine infrastructure and operation and maintenance (O&M); the lower row shows the share of total project capital cost attributable to seabed foundations in the fixed-bottom project and to floating substructures and mooring systems in the floating project. (c) Trends toward larger turbines, deeper water, and more complex seabed conditions.

This lifecycle can be broadly divided into four primary stages, each of which presents distinct geotechnical challenges (**Fig. 2**). (1) During site investigation, high offshore operational costs and narrow weather windows often restrict borehole and in-situ testing density, leaving sparse and spatially discontinuous subsurface information [8,9]. (2) During design, foundation and anchoring systems are subjected to nonlinear and cyclic loading under uncertain ground conditions, making soil-structure interaction and long-term stability key concerns [10,11]. (3) During installation, penetration response is highly sensitive to local stratigraphic variability, which may trigger construction hazards such as pile refusal, excessive inclination, or spudcan

punch-through [2,3]. (4) During O&M, scour evolution and changes in foundation condition remain partly hidden during service, complicating long-term performance assessment [12,13]. These stage-specific problems are linked by shared constraints in data availability, governing mechanisms, and decision requirements, making it difficult for any single analytical framework to simultaneously satisfy accuracy, efficiency, and engineering interpretability across all phases.

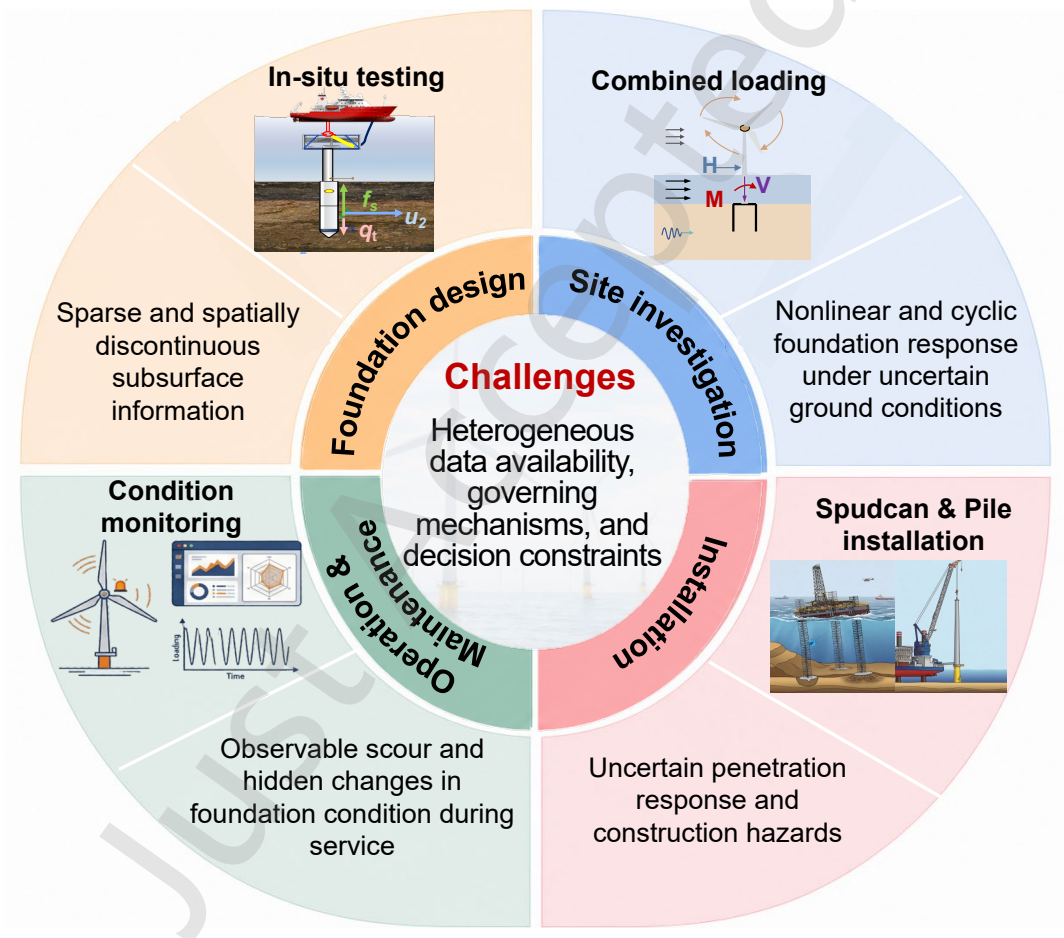


Fig. 2. Geotechnical challenges and shared constraints across the offshore wind lifecycle.

Current offshore geotechnical practice draws on multiple established approaches to address different engineering questions [2,14–16]. Empirical design formulations efficiently support routine design checks using representative parameters and simplified response relationships. Numerical simulations provide detailed representations of nonlinear soil–foundation interaction and complex loading paths

[17–19]. Probabilistic analyses quantify parameter uncertainty and, when coupled with spatial models, represent spatial variation in ground conditions across a site [16]. Analytical solutions, limit-analysis methods, and other established techniques also contribute to geotechnical assessment. Collectively, this broader set of methods provides the analytical foundation for geotechnical decision-making.

Alongside these established methods, AI approaches, particularly machine learning, have increasingly been explored as complementary tools in offshore wind geotechnics. Their potential contributions can be organized into three related functions. First, machine learning can support multi-source data fusion by integrating in-situ tests and geophysical surveys to characterize spatially variable ground conditions across offshore sites [20,21]. Second, AI-based surrogate models can learn input–response relationships from numerical or experimental datasets, reducing the cost of repeated response and reliability analyses and supporting parametric studies, probabilistic assessment, and rapid foundation-response prediction [22–24]. Third, monitoring-informed learning and probabilistic updating can assess installation response, track scour evolution, and infer changes in foundation condition below the seabed during operation. The relevance of each function depends on data availability, governing mechanisms, and decision requirements across lifecycle stages. **Table 1** summarizes the main lifecycle-stage geotechnical issues and representative AI application roles.

Table 1. Main geotechnical challenges and representative AI application directions across the offshore wind project lifecycle.

Lifecycle stage	Main geotechnical challenge	Representative AI application direction
Site investigation	Sparse and spatially discontinuous subsurface information	Stratigraphic interpretation, parameter identification, and spatial ground modeling
Foundation design	Nonlinear, cyclic, and reliability-sensitive foundation response under uncertain ground conditions	Rapid prediction, cyclic response assessment, and reliability/optimization support

Lifecycle stage	Main geotechnical challenge	Representative AI application direction
Installation	Uncertain penetration response and construction hazards under stratigraphic variability	Penetration prediction/updating, and hazard screening
Operation and maintenance	Hidden evolution of scour and foundation condition during service	Scour assessment/prediction, condition assessment, and state updating

Recent reviews and application studies document growing use of AI in geotechnical engineering and offshore wind foundation analysis [14,15,22,23]. Several review gaps nevertheless remain. (1) Most existing reviews focus on general geotechnical problems rather than offshore wind specific challenges. (2) Prior studies are often organized by algorithm type, which can obscure the links among geotechnical mechanisms, AI functions, and lifecycle-stage requirements. (3) Limited attention has been given to practical deployment in real offshore wind projects. (4) Emerging workflow-oriented AI paradigms, including agent-assisted modeling and engineering automation, remain underexplored in offshore geotechnical contexts.

To address these gaps, this paper presents a lifecycle-oriented review of AI applications in offshore wind geotechnical engineering, covering studies published between 2001 and 2025 and selected project- and industry-level practices. It first establishes the literature basis and broad research patterns, then synthesizes lifecycle-stage applications and compares their maturity across stages and task types. The review further identifies cross-cutting limitations related to data quality, physical constraints, generalizability, standardization, and engineering acceptance. Finally, it outlines several possible future directions, including physics-integrated learning and agent-assisted workflows, to support more reliable and cost-effective offshore wind development.

2 Literature Screening and Analysis

This section establishes the dataset and analytical framework for the review. Because research on AI in offshore wind geotechnical engineering spans multiple disciplines and uses heterogeneous terminology, a unified search, screening, and classification procedure was

adopted. The section first introduces the search and screening strategy, then presents the classification framework and bibliometric characteristics of the final dataset.

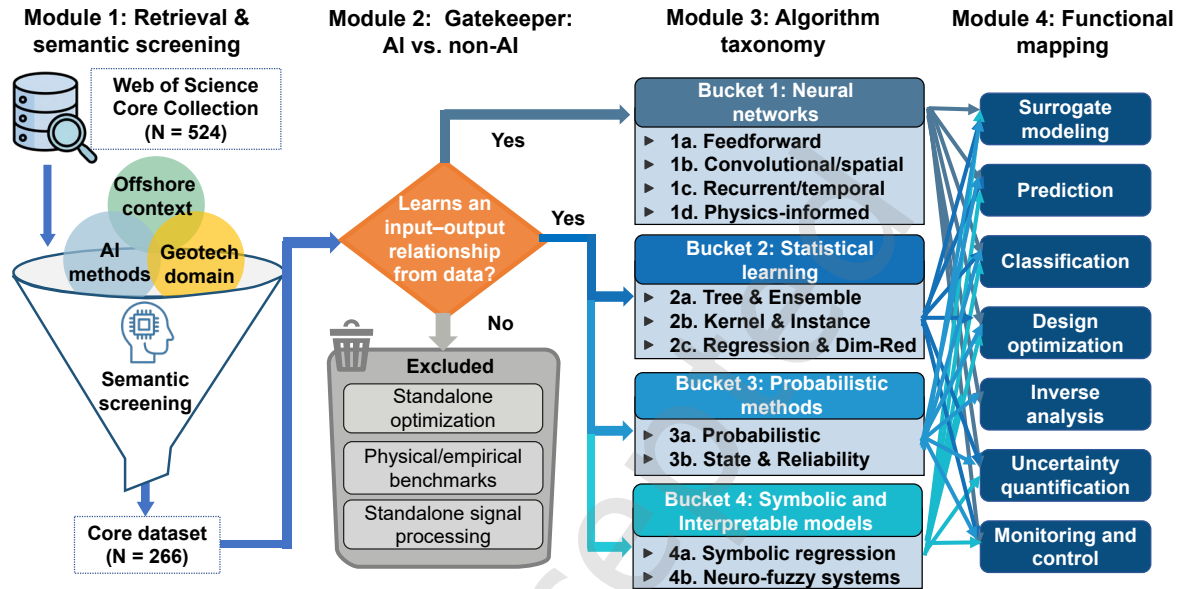


Fig. 3. Literature screening workflow.

2.1 Semantic logic-based search and screening

2.1.1 Search strategy

A systematic literature review framework was employed to identify, screen, classify, and quantitatively analyze research on AI in offshore wind geotechnical engineering. Literature retrieval was conducted in the Web of Science Core Collection for the period from January 1, 2001 to December 31, 2025. Given the interdisciplinary nature of the topic, keyword-only searches risk both omission and irrelevant retrieval. To improve coverage while reducing cross-disciplinary retrieval noise, a three-pillar semantic strategy was adopted:

- Pillar A (algorithm dimension): AI, statistical learning, and probabilistic learning methods;
- Pillar B (engineering context): offshore wind, marine foundations, and related systems;
- Pillar C (geotechnical mechanics): soil behavior, response mechanisms,

and typical offshore geotechnical problems.

The detailed search strings are provided in the **Supplementary Material**. The overall workflow is illustrated in **Fig. 3**.

2.1.2 Screening process and criteria

To ensure dataset consistency and reduce cross-disciplinary misclassification, inclusion and exclusion criteria were defined across five dimensions: application scenario, research object, core problem, research method, and publication type, as summarized in **Table 2**.

Based on established definitions of AI that emphasize learning from data and applying the learned relationships to specific tasks ^[25,26], research-method eligibility required a model or an input–output relationship to be learned from data. Methods that did not meet this criterion, such as standalone optimization, purely physical or empirical analyses, and signal-processing methods without an accompanying learned model, were excluded as specified in **Table 2**.

The screening followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines ^[27]. The initial search yielded 524 records. After applying the criteria in **Table 2**, a final dataset of 266 papers was obtained, forming the basis for the subsequent classification and bibliometric analyses. Supplementary reviews and industry sources, including examples from adjacent structural and operational systems, provide contextual evidence and are excluded from the 266-study screened corpus.

Table 2. Inclusion and exclusion criteria for literature screening

Dimension	Inclusion criteria	Exclusion criteria
Application scenario	Explicitly related to offshore wind or the broader marine engineering context; involving offshore or nearshore geology and foundation engineering	General civil engineering scenarios unless transferability was clearly demonstrated; fully onshore or non-marine contexts
Research object	Offshore wind foundations (e.g., monopiles, pile groups, suction caisson foundations, gravity-based foundations), anchoring and mooring systems, seabed	Upper turbine structures, submarine cables, and other purely structural or electrical components

Dimension	Inclusion criteria	Exclusion criteria
Core problem	soils, and investigation or monitoring data (e.g., CPT, boreholes, in-situ test data)	
	Site investigation and identification, ultimate bearing capacity, settlement and deformation, installation response, scour protection, hazard-risk assessment, and condition assessment involving soil–structure interaction	Structural fatigue or fracture unrelated to soil–foundation interaction; aerodynamic or hydrodynamic load analysis; grid dispatch; energy capture
Research method	Data-driven algorithms trained to establish input–output relationships, including neural networks, statistical learning, probabilistic models, and symbolic regression	(1) Pure optimization algorithms such as GA, PSO, and SA unless GP/GEP was used to generate explicit formulae; (2) purely physical or empirical baselines such as FEM, API/DNV methods, and analytical solutions; (3) pure signal-processing methods such as FFT and VMD unless combined with neural networks
Publication type	Peer-reviewed journal and conference papers	Reviews, editorials, abstract collections, and grey literature

2.2 Classification framework

To systematically characterize AI applications, the reviewed studies were interpreted along three complementary dimensions: algorithm type, engineering function, and lifecycle stage. This framework reflects the fact that the same method may serve different roles depending on data conditions and engineering objective.

2.2.1 Algorithm classification

Algorithms were categorized into four groups: (1) neural networks, including feedforward, convolutional, recurrent, and physics-informed or hybrid architectures; (2) statistical learning, including tree-based ensembles, kernel- or instance-based methods, and regression or dimensionality-reduction techniques; (3) probabilistic methods, including probabilistic learning, state estimation, and reliability updating; and (4) symbolic and interpretable models, represented mainly by evolutionary symbolic regression and neuro-fuzzy systems.

2.2.2 Functional classification of engineering applications

Seven functional labels were assigned according to the engineering role of the learned model: surrogate modeling, prediction, classification, optimization-oriented applications, inverse analysis, uncertainty quantification (UQ), and monitoring and control. Among the included studies, the optimization-oriented label was assigned when a learned model guided the search for an engineering design, consistent with surrogate-based optimization [28]. Optimization used solely to train a model did not trigger this label. Multi-step studies were assigned multiple functional labels where appropriate.

2.2.3 Lifecycle classification

Studies were further categorized into four lifecycle stages on their primary engineering focus: (1) site investigation, involving stratigraphic interpretation, parameter identification, and spatial ground modeling; (2) foundation design, including bearing capacity, deformation, cyclic response, and reliability assessment; (3) installation, including penetration response, installation risk, and construction control; and (4) operation and maintenance (O&M), involving scour evolution, condition assessment, and state updating during service. Studies spanning multiple stages were assigned to the dominant stage.

2.2.4 Quantitative performance-evidence synthesis

Bibliometric counts indicate where AI has been applied, but they do not show what data support the reported model performance or how that performance was evaluated. We therefore assembled a stage-specific quantitative evidence set from original studies with accessible full text, extractable evaluation results, and tasks aligned with the four lifecycle stages. After screening, 240 studies contributed 3,003 model--target--metric--evaluation records. For each record, we coded the prediction target, training-data source, performance metric and unit, and validation setting. The extracted metrics covered R^2 , error, classification, correlation, and task-specific measures; training sources were grouped as numerical simulation, field, laboratory, secondary or public, hybrid, or analytical/synthetic data. Validation evidence was

coded as internal/unclear, cross-validation, same-source holdout, other external, or field-case evaluation. For each study--metric--unit combination, only results from the highest available evaluation level were retained. Tables 4-7 present the stage-level comparisons of training sources, reported performance, and validation, while Supplementary Tables S2-S5 provide detailed metric- and unit-specific results.

2.3 Bibliometric analysis

Based on the 266 bibliometric records published from 2001 to 2025, AI applications in offshore wind geotechnical engineering have expanded both in number and in scope. Trends are analyzed from four perspectives: overall growth, algorithm evolution, functional applications, and lifecycle coverage.

2.3.1 Overall trends

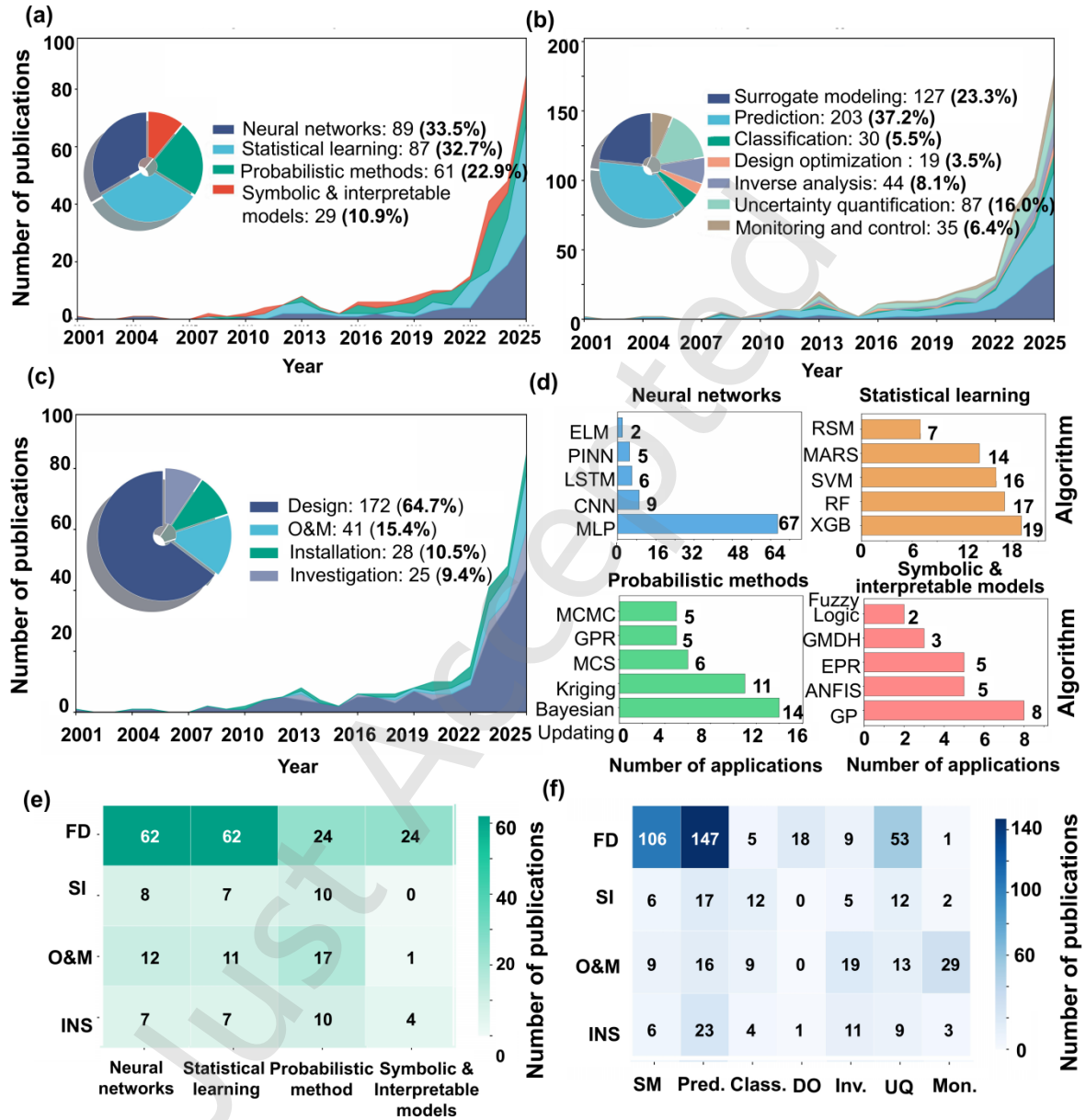


Fig. 4. Developmental trends and category distributions of AI applications in offshore wind geotechnical engineering. (a) Annual publication counts by AI paradigm. (b) Annual distribution of application tasks. (c) Annual distribution across lifecycle stages. (d) Representative algorithms used in different AI paradigms. (e) Relationship between AI paradigms and lifecycle stages. (f) Relationship between application tasks and lifecycle stages. Lifecycle and function abbreviations: SI,

site investigation; FD, foundation design; INS, installation; O&M, operation and maintenance; SM, surrogate modeling; Pred., prediction; Class., classification; DO, design optimization; Inv., inverse analysis; UQ, uncertainty quantification; Mon., monitoring and control. Algorithm abbreviations: ELM, extreme learning machine; PINN, physics-informed neural network; LSTM, long short-term memory; CNN, convolutional neural network; MLP, multilayer perceptron; RSM, response surface method; MARS, multivariate adaptive regression splines; SVM, support vector machine; RF, random forest; XGB, extreme gradient boosting; MCMC, Markov chain Monte Carlo; GPR, Gaussian process regression; MCS, Monte Carlo simulation; GMDH, group method of data handling; EPR, evolutionary polynomial regression; ANFIS, adaptive neuro-fuzzy inference system; GP, genetic programming.

As shown in **Fig. 4a**, **research** development can be divided into three stages. The early exploration stage (2001–2010) accounted for approximately 3% of studies and was dominated by small-sample proof-of-concept work. The accumulation stage (2011–2015) contributed 8.7%, reflecting gradual adoption of data-driven methods. The rapid growth stage (2016–2025) accounted for 88.4%, with 74.8% (199 papers) published between 2021 and 2025.

This growth occurred within the wider expansion of AI across scientific and engineering fields, supported by advances in learning algorithms, greater data availability, and computational resources [29–31]. Within offshore wind geotechnics, larger turbines and deeper-water projects provide an important application context because foundation analyses must address more complex loading and soil–structure interaction [15,19]. Established numerical methods and data-driven models serve complementary roles: numerical methods represent physical mechanisms and provide high-fidelity simulations, while data-driven models support rapid prediction and repeated surrogate evaluations [24,31].

2.3.2 Trends in algorithm evolution

As illustrated in **Fig. 4a** and **Fig. 4d**, **neural** networks (33.5%) and statistical learning (32.7%) dominate current applications, followed by probabilistic methods (22.9%).

Multi-Layer Perceptrons (MLPs) represent the most commonly used neural network architecture (44.9% of neural networks), largely due to their implementation simplicity. However, their performance remains sensitive to data quantity and coverage, which is a recurring issue in offshore geotechnics. Statistical learning algorithms (e.g., XGBoost, random forests, and support vector machines) remain widely used for small- to medium-sized tabular datasets, while the growth of probabilistic methods (e.g., Kriging, Gaussian process regression) reflects increasing attention to uncertainty-aware modeling required for spatial variability characterization and reliability analysis.

2.3.3 Trends in functional applications

Fig. 4b shows that prediction dominates (76.3%), followed by surrogate modeling (47.7%) and uncertainty quantification (32.7%). Prediction remains prevalent because many studies focus on rapid mappings between input parameters and target responses, such as bearing capacity, deformation, dynamic response, or scour development. The prominence of surrogate modeling reflects its use in reducing the need for repeated high-cost numerical simulations. The growing role of UQ indicates a transition from deterministic prediction toward risk-informed decision support, particularly in uncertain geotechnical environments with geological complexity or operationally sensitive settings. These results suggest that AI in this field has evolved from rapid response estimation toward broader support for risk analysis and engineering decision-making.

2.3.4 Lifecycle distribution and evolution

As shown in **Fig. 4c**, **foundation** design accounts for 64.7% of the original 266-record corpus, compared with 9.4% for site investigation, 10.5% for installation, and 15.4% for O&M. To test whether this concentration reflected terminology bias, we conducted two supplementary Web of Science Topic searches using installation- and O&M-specific terms under the original eligibility criteria. Of the 1,301 retrieved records, 810 new candidates remained after bibliographic filtering, deduplication, and matching with the original corpus. Most addressed

upper-structure, turbine-component, or mooring-line monitoring rather than direct geotechnical targets. Three additional studies met the eligibility criteria: one installation study and two O&M studies [32–34]. Adding these studies formed a 269-record sensitivity set; the foundation-design share was 63.9%, and the lifecycle ranking remained unchanged. This stability supports the robustness of the original search strategy to the tested terminology expansion; accordingly, the 266-record corpus was retained for the primary bibliometric analyses. The complete search strings and search-pool sensitivity evidence are provided in Supplementary Section S1 and Table S1.

Overall, AI applications in offshore wind geotechnics exhibit distinct patterns across algorithms, functions, and lifecycle stages. Methodologically, neural networks, statistical learning, and probabilistic approaches dominate. Functionally, the field has evolved from deterministic rapid prediction toward surrogate modeling, uncertainty quantification, and decision support. Regarding lifecycle distribution, research remains heavily concentrated in the design phase, while site investigation, installation, and O&M face greater data and deployment constraints. However, bibliometric analysis alone cannot explain how differences in geotechnical mechanisms, data structures, and engineering requirements shape AI applicability across lifecycle stages. Because each stage involves distinct physical processes and decision contexts, Section 3 adopts a lifecycle-oriented perspective to examine main AI applications and their limitations in detail.

3 Applications of AI Across the Lifecycle

3.1 Site Investigation

As offshore wind development advances into deeper waters, site investigations must cover larger seabed areas with stronger spatial variability [35]. In practice, however, offshore campaigns are constrained by limited weather windows and high drilling costs, resulting in sparse boreholes and cone penetration tests (CPTs) and leaving significant gaps in subsurface characterization [9]. This creates a fundamental challenge: sparse data must still support the

level of ground characterization required for foundation design. For systems such as floating anchors and large-diameter monopiles, both ultimate resistance and long-term response depend strongly on local ground conditions around the foundation^[36,37]. While increasing investigation density can reduce uncertainty, it is often economically infeasible.

To address this gap, AI applications in site investigation have mainly developed along two directions. The first focuses on interpreting sparse vertical sounding data, where machine learning and probabilistic frameworks enhance soil classification and uncertainty-aware parameter estimation (e.g., from CPT). The second addresses site-scale spatial reconstruction, where multi-source data fusion integrates geophysical and geotechnical information to infer continuous full-site subsurface models. In both cases, the central objective is to bridge the gap between limited measurements and the level of subsurface understanding required for engineering decision-making.

3.1.1 AI-assisted interpretation of sparse sounding data

Offshore site investigation data, especially CPT records, are often sparse, noisy, and one-dimensional. A key challenge lies in identifying stratigraphic boundaries reliably. Traditional deterministic approaches, such as the Robertson chart, can perform poorly in transitional soils and thin interbedded strata^[38]. To address this limitation, probabilistic classification methods have been introduced, representing stratigraphy in terms of uncertainty rather than fixed class labels. Approaches like Bayesian mixture models and weighted k-nearest neighbors have been used to represent soil classification through posterior probabilities or entropy-based measures^[39,40].

Since marine deposits exhibit strong depositional ordering and vertical correlation, sequence-aware models are more suitable than pointwise classifiers. Methods such as hidden Markov models (HMMs) and bidirectional long short-term memory networks (Bi-LSTMs) incorporate sequential dependencies to reduce spurious discontinuities and improve recognition of thin interbeds^[41–43].

Following stratigraphic interpretation, parameter estimation becomes critical for

design. Traditional empirical correlations, such as estimating undrained shear strength from cone resistance q_c , often struggle to capture nonlinear soil behavior. Data-driven regression models, especially ensemble methods such as random forest and XGBoost, have therefore been used to learn nonlinear mappings directly from CPT-derived features without predefined functional forms [44,45].

To mitigate data scarcity in deep-water environments, several complementary strategies have emerged. Generative models, including generative adversarial networks (GANs) and variational autoencoders (VAEs), can augment limited geotechnical datasets [46,47], while semi-supervised learning can use unlabeled offshore survey data to improve parameter estimation [48]. Bayesian hierarchical approaches further integrate sparse local measurements with regional geological knowledge [49,50]. Collectively, these methods improve the reliability of interpreted vertical soil profiles and support downstream site-scale modeling.

3.1.2 Spatial reconstruction from multi-source survey data

As offshore sites become larger and more heterogeneous, sparse boreholes and CPTs are insufficient to characterize full spatial variability. Traditional geostatistical interpolation methods (e.g., Kriging) rely on distance-based smoothing and often fail to capture abrupt stratigraphic changes. Similarly, machine learning models trained solely on CPT data tend to produce locally biased predictions and perform poorly in under-sampled regions [24,46]. To address these limitations, geophysical-geotechnical (G&G) data fusion has emerged as a key strategy. By combining the wide spatial coverage of seismic or acoustic surveys with localized geotechnical measurements, such fusion workflows enable reconstruction of 2D or 3D subsurface property fields across entire sites [51] (**Fig. 5a**).

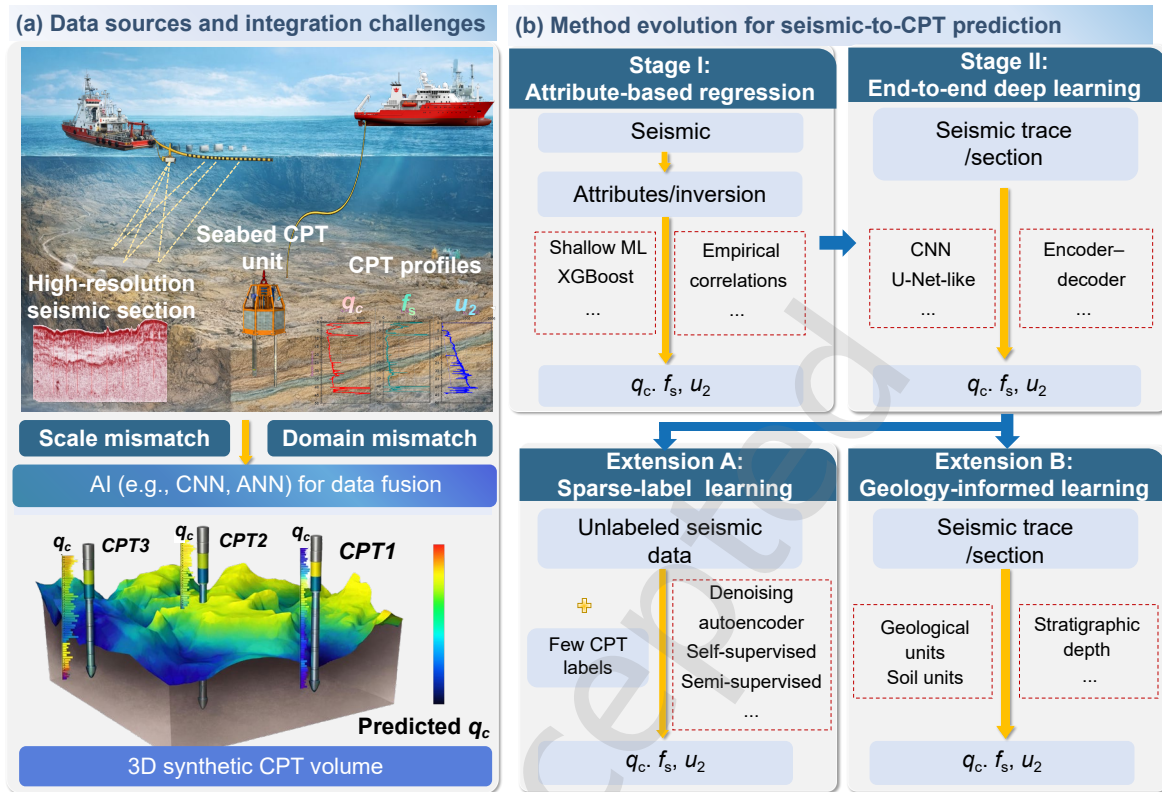


Fig. 5. AI-enabled seismic–CPT integration for offshore site characterization. (a) Data sources, integration challenges, and representative fused outputs. (b) Evolution from attribute-based regression to end-to-end deep learning, together with two current directions involving sparse-label and geology-informed learning. Abbreviations: AI, artificial intelligence; CPT, cone penetration test; ANN, artificial neural network; CNN, convolutional neural network; ML, machine learning; q_c , cone resistance; f_s , sleeve friction; u_2 , pore-water pressure measured at the cone shoulder.

A central challenge in G&G fusion is that geophysical signals do not directly correspond to geotechnical parameters such as cone resistance or shear strength. Their relationship is usually indirect, nonlinear, and site dependent ^[20]. Early workflows therefore often followed a multi-step procedure (**Fig. 5b**): seismic attributes (e.g., acoustic impedance) were first extracted, then mapped to geotechnical parameters (e.g., q_c and s_u) using machine learning models, and finally extrapolated spatially (2D or 3D) ^[20,52]. While useful, these pipelines are vulnerable to cumulative error due to their multi-stage nature.

To reduce such error propagation, recent advances have shifted toward end-to-end deep learning, where convolutional neural networks (CNNs) directly map seismic data to geotechnical parameters. These approaches reduce intermediate steps and better capture spatial structure, demonstrating improved performance in subsurface prediction tasks [48,53–56]. Extensions incorporating neighborhood aggregation and deep encoding further enhance prediction in deeper strata, where signal attenuation is significant [48,53,54,57].

Despite these advances, purely data-driven fusion remains constrained in deep-water settings. Limited CPT data increases overfitting risk, while issues like seismic misties, time-depth conversion bias, and vertical resolution mismatch reduce model robustness (**Fig. 5a**). Current work therefore focuses on two directions: (1) integrating physically informed treatments, such as adaptive time-depth conversion, together with geological constraints, such as sequence-stratigraphic guidance [48,58,59], and (2) leveraging semi-supervised, denoising strategies, and generative models to expand effective training datasets with large volumes of partially labeled or unlabeled data [21,47,60,61].

At the engineering level, multi-source spatial reconstruction is evolving beyond deterministic point prediction toward uncertainty-aware site assessment. By quantifying predictive uncertainty (e.g., entropy-based measures), AI models can identify low-confidence regions and guide additional borehole placement [40,62]. Combined with GIS-based spatial analysis, these approaches also support mapping of seabed geohazards, including liquefaction susceptibility [63,64]. Overall, AI-driven multi-source fusion enables a transition from discrete-point interpretation to continuous, site-scale geological modeling and risk screening (**Fig. 5b**). Representative engineering applications of AI-enabled CPT-seismic fusion and multi-source prediction in offshore projects are summarized in **Table 3**.

Table 3. Representative offshore applications of AI-enabled CPT fusion and multi-source prediction

Project / location	Method	Data	Output / engineering use	Status	Ref
Hollandse Kust West, Netherlands	CNN	122 CPTs + 162 2D UHR seismic lines	3D voxel model of q_c and $G_{\max}$ from 1.5 million synthetic CPTs for government tender delivery	Official tender deliverable	[65]
Hollandse Kust West, Netherlands	Supervised neural network	2D UHR MCS + seafloor CPTs	Synthetic CPT (q_c) profiles with uncertainty bands for tender support	Official tender deliverable	[66]
IJmuiden Ver Gamma, Netherlands	ANN	5,450 km 2D UHRS + 115 CPTs	Full-site design-parameter profiles (s_u, ϕ) with confidence classes A–E	Official tender deliverable	[67]
Ten Noorden van de Waddeneilanden, Netherlands	XGBoost	3D UHRS volumes + CPT data	q_c prediction with automatic depth-shift correction; outperformed linear regression	Industry-led validation	[58]
Hollandse Kust Zuid, Netherlands	ANN	2D sparker seismic + 23 CPTUs	q_c prediction for monopile diameter/length optimization; better than Kriging	Industry-led validation	[68]
Hollandse Kust Zuid, Netherlands	CNN	125 2D UHRS lines + 50 CPTs	Direct prediction of q_c , f_s , and u_2 from seismic; improved thin-layer detection	Industry-led validation	[48]
Borssele III & IV, Netherlands	CNN	55 2D lines + 66 CPTs	Physics-guided prediction with geological constraints to reduce noise and improve realism	Industry-led validation	[48]
German North Sea	Ensemble FNN	30–40 CPTs + 2D MCS	Pore-pressure (u_2) prediction for hazardous clay-layer identification	Industry-led validation	[62]

Project / location	Method	Data	Output / engineering use	Status	Ref
Atlantic Shores, USA	CNN	64 CPTs + ~200 2D UHRS lines	Direct q_c prediction to reduce reliance on dense physical testing	Industry- academia validation	[54]
Yinggehai Basin, China	CNN	60 CPTs + 361 2D sparker lines	Deep-strata prediction with low error (RMSE 5.14 MPa) below 20 m	Industry- academia validation	[53]
Northern Irish Sea, Ireland	ANN	24 CPTs (19 used) + coordinates/depth	Synthetic CPT generation for spatial interpolation; best performance in homogeneous muds	Industry- academia validation	[69]

3.1.3 Engineering practice and digital ground-model development

As offshore site investigation moves into deeper water, AI-enabled virtual CPT generation and geophysical inversion are progressing from methodological development to project-scale implementation. A prominent example is the Hollandse Kust West project in the Netherlands, where a CNN-based workflow was used to generate approximately 1.5 million synthetic CPT profiles and convert them into a 3D voxel model containing continuous geotechnical information for a government tender package [65]. This project has been cited by DNV as an important step toward practical AI-enabled geotechnical site investigation.

Another example is the IJmuiden Ver Gamma project, where ensemble neural networks were combined with elastic-impedance inversion to generate full-site design-parameter profiles with five confidence levels [67]. These cases indicate that AI-based site investigation is no longer confined to proof-of-concept studies, but is beginning to support tendering, site screening, and design-oriented digital ground modeling.

Related developments are also evident in digital ground-model platforms such as Fugro's Gaia system, and in the growing use of shipboard real-time data analytics and machine learning to identify weak layers, boulder occurrence, and local foundation risk zones during offshore campaigns [70–72]. These developments suggest that site

investigation is moving toward integrated digital workflows where data acquisition, inversion, interpretation, and engineering decision support are increasingly connected.

3.1.4 AI model training and evaluation in site investigation

Site-investigation evidence is strongly field-oriented, but field-based training has not yet translated into equally strong evidence of spatial transfer. Thirteen of the 22 studies used field data, and none used numerical simulation as the primary training source. Nevertheless, only one field-trained study reported R^2 , with values of 0.44–0.68 under same-source holdout validation (Table 4). Field provenance therefore shows that models learn from real observations, but it does not demonstrate performance beyond the development site. Current evidence supports parameter and profile prediction within characterized sites, while performance across independent sites remains sparsely tested.

Table 4. Training source, validation, and R^2 in site-investigation studies.

Training data	All studies, n (%)	R^2 studies, n	Validation of reported R^2	Reported R^2	Mean R^2
Numerical simulation	0 (0.0)	0	Not reported	Not reported	Not reported
Field data	13 (59.1)	1	Same-source holdout (1)	0.440–0.680	0.560
Other sources	9 (40.9)	4	Same-source holdout (2); field case (1); internal/unclear (1)	Holdout: 0.947–0.962; field case: 0.990; internal/unclear: 0.126–0.992	0.908

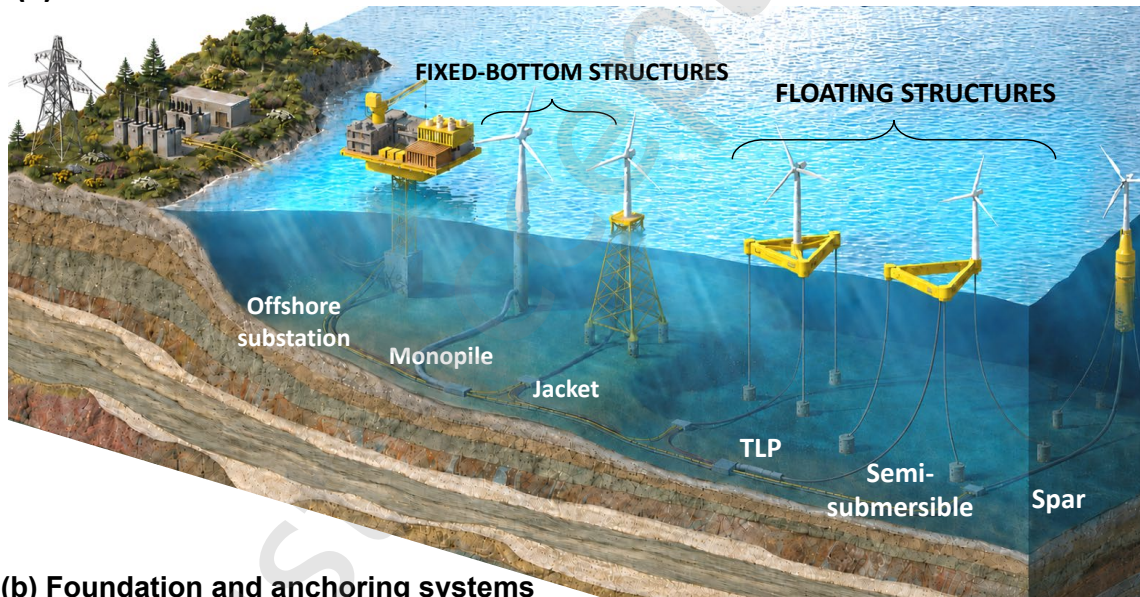
Note: Mean R^2 is the unweighted mean of study-level representative values. Other sources combine laboratory, secondary or public database, hybrid, and synthetic or analytical data. Detailed results: Supplementary Table S2.

3.2 Foundation design

Offshore wind foundation design is no longer limited to static ultimate-capacity checks [73]. For large-diameter monopiles, suction caisson foundations, and deep-water anchoring systems such as suction anchors, design must also address serviceability, cyclic degradation, cumulative displacement, and long-term stability under repeated environmental loading (Fig. 6).

The terms suction caisson and suction bucket refer to the same basic open-bottomed, closed-top cylindrical structure installed by pumping water from its interior to create a pressure difference ^[74]. When the structure directly supports a fixed-bottom substructure, it is commonly termed a suction caisson foundation or suction bucket foundation; this review uses suction caisson foundation consistently. When the same type of structure anchors a floating system through a mooring line, it is termed a suction anchor ^[75]. A suction bucket jacket is a fixed-bottom jacket supported by multiple suction caisson foundations ^[76].

(a) Offshore wind farm



(b) Foundation and anchoring systems

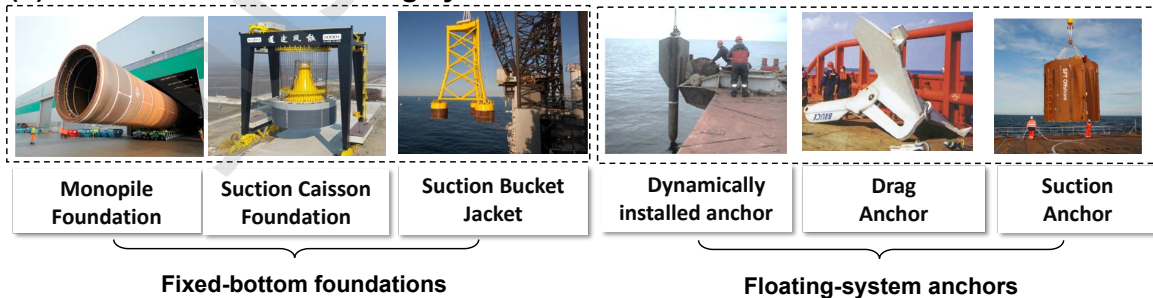


Fig. 6. Representative offshore wind support structures, foundation systems, and seabed anchors. (a) Fixed-bottom and floating support structures shown schematically across increasing water depths. (b) Representative fixed-bottom foundations and seabed anchors for floating systems (adapted from ^[76–81]). TLP, tension-leg platform.

Across these foundation and anchoring systems, design problems are still commonly assessed using analytical or semi-empirical frameworks, such as the Winkler p - y method for monopiles^[82] and V-H-M macro-yield envelopes for suction caisson foundations^[83]. As foundation sizes increase, loading histories become longer, and seabed conditions become more complex, repeated application of these methods can require substantial calibration or computational effort^[84–87]. Within this setting, AI is being used as a complementary tool in three main ways: rapid prediction of nonlinear capacity and response, modeling of cyclic and time-dependent behavior, and support for reliability-based design and optimization. These technical routes are summarized in **Fig. 7**.

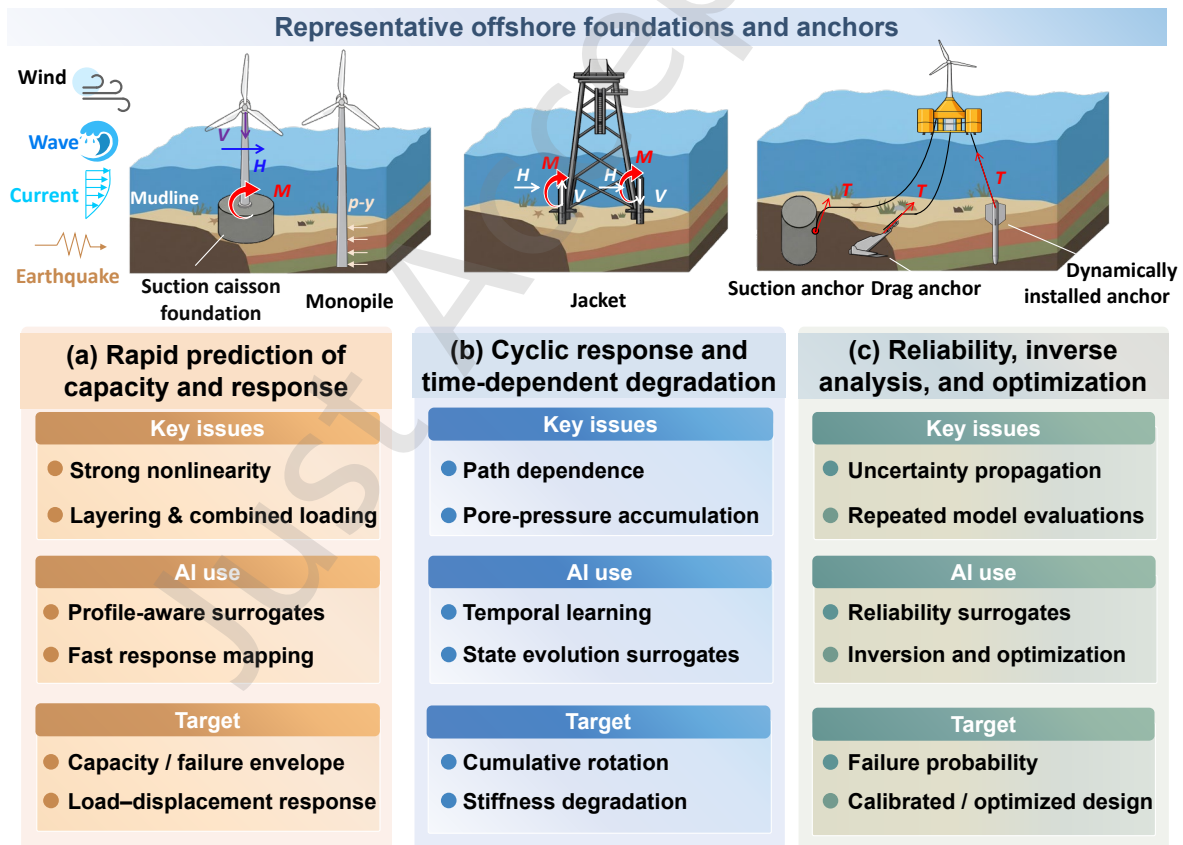


Fig. 7. AI-assisted technical routes across offshore wind foundation and anchor design. The upper schematics show representative fixed-bottom foundations and floating-system anchors under environmental loading; the lower panels summarize three cross-cutting applications. (a) Rapid prediction of capacity, failure envelopes, and load-displacement response. (b) Modeling of cyclic

response and time-dependent degradation. (c) Surrogate-assisted reliability assessment, inverse analysis, and design optimization. H , horizontal load; V , vertical load; M , moment; T , mooring-line tension; p - y , lateral soil resistance–displacement relation.

3.2.1 Rapid prediction of foundation capacity and response

A central role of AI in offshore wind foundation design is to provide fast predictive or surrogate models for capacity, failure envelopes, and load-displacement response, thereby reducing the need for repeated high-cost numerical analyses. This is particularly valuable because offshore foundations are often subjected to nonlinear soil-structure interaction, layered seabeds, and combined loading, making direct high-fidelity simulation too expensive for routine design iteration.

Large-diameter monopiles. Large-diameter monopiles remain the dominant foundation type in offshore wind engineering^[88], and their design is often governed by lateral loading and overturning moment rather than by vertical resistance alone^[89]. As a result, methods developed for smaller piles or simplified loading assumptions become increasingly inadequate for layered soils and large-diameter behavior^[17,90]. In particular, the classical p - y approach was developed mainly for smaller-diameter flexible piles^[82,90], whereas large-diameter monopiles tend to exhibit stiffer, more rotation-dominated response, with greater contributions from shallow three-dimensional failure, base shear, and moment resistance^[89,91]. Frameworks such as the PISA model have improved this situation^[37,92], but they still rely strongly on site-specific calibration and are not always easy to generalize in layered or spatially variable soils. This has motivated AI-assisted surrogate modeling based on finite-element and related numerical datasets. Recent studies have moved beyond simple scalar descriptors by using full depth-varying soil profiles directly as model input, for example through one-dimensional CNNs that better capture stratigraphic effects on lateral resistance^[93,94]. Physics-informed and multi-fidelity strategies have further been explored to improve computational efficiency while preserving physical

credibility ^[95,96]. Li et al. ^[97] combined long short-term memory networks for p–y curve extrapolation with symbolic regression for initial stiffness and ultimate resistance. In a complementary study, they coupled XGBoost predictions of soil springs with physics-informed neural networks to solve pile bending equations incorporating base resistance ^[98]. Overall, monopile lateral-response modeling is evolving from empirical beam-on-Winkler formulations toward AI-assisted frameworks calibrated against high-fidelity analysis and better suited to layered soils and large-diameter behavior ^[91,99–102] (**Fig. 7a**).

Suction caisson foundations and suction anchors. Suction caisson foundations used as support foundations and suction anchors used for floating systems share several common design issues, including uplift resistance and combined vertical-horizontal-moment (V-H-M) loading ^[103,104]. Under uniaxial uplift, early studies mainly used ANN-based models to establish implicit mappings between soil parameters and uplift capacity ^[105–107]. Later work introduced more interpretable or uncertainty-aware methods, including symbolic regression and Bayesian inference ^[108–112]. In fixed-bottom applications, especially for low-aspect-ratio suction caisson foundations, design is often governed by combined V-H-M loading, for which scalar capacity values are insufficient and three-dimensional failure envelopes become more important. Because direct finite-element evaluation in multidimensional load space is expensive, surrogate models trained on high-fidelity numerical samples have increasingly been used to reconstruct these envelopes, often by combining finite-element limit analysis with machine-learning models such as XGBoost ^[23,113–116]. Thus, AI applications for suction caisson foundations and suction anchors have progressed from single-value uplift prediction to nonlinear failure-envelope reconstruction under combined loading, with growing extension to broader scenario analysis ^[117–120].

Other deep-water anchoring systems. As floating offshore wind expands into deeper water, other anchoring systems such as plate anchors, helical anchors, and

dynamically installed anchors are receiving growing attention. Their behavior commonly involves deep embedment, inclined pullout, dynamic installation, and large deformation, all of which make repeated high-fidelity analysis computationally demanding. Existing studies therefore focus mainly on rapid prediction of local bearing response and failure boundaries. Hybrid methods that combine machine-learning surrogates with finite-element limit analysis or isogeometric analysis have been used to construct stability charts and predict anchor behavior in anisotropic or layered soils ^[121–125]. Symbolic regression has also been used to derive an associative yield function for suction-embedded plate anchors under combined loading ^[126]. For more complex anchor geometries, data-driven and hybrid methods have also been applied to map soil parameters to uplift resistance ^[127–129]. These studies confirm the value of AI for accelerating design calculations, but also show that predictive robustness remains sensitive to the coverage of the training domain, especially when anchor geometry, loading angle, or failure mechanism changes significantly ^[130,131].

3.2.2 Cyclic response, serviceability, and time-dependent degradation

Another major challenge in offshore wind foundation design is that long-term performance is often governed not by a single ultimate event, but by the gradual accumulation of deformation and stiffness loss under repeated loading. Serviceability assessment has therefore become as important as ultimate capacity in many cases. Cyclic loading from waves, turbine operation, and environmental variability may lead to ratcheting displacement, stiffness degradation, gapping, pore-pressure accumulation, and progressive changes in failure resistance ^[17,18,84–86]. These effects are strongly path dependent and difficult to represent using static design formulations alone (**Fig. 7b**).

For large-diameter monopiles, cyclic loading over a 20–25 year service life may result in cumulative rotation, stiffness reduction, and pile-soil gapping ^[84–86]. Static p – y formulations are not well suited to this kind of history-dependent evolution. Sequence-based and temporal learning models, including LSTM-type architectures

with internal memory, have therefore increasingly been explored to represent cyclic stiffness evolution and accumulated response ^[17,18] (**Fig. 7b**).

For suction caisson foundations and suction anchors, cyclic loading may alter both stiffness and failure boundaries, although the dominant loading form differs with engineering context; installation effects may also influence subsequent foundation performance ^[132]. In suction caisson foundations, repeated loading can drive pore-pressure accumulation and gradual resistance degradation, so the relevant design quantity becomes not a fixed failure envelope but its time-dependent evolution ^[133]. In suction anchors used in floating mooring systems, cyclic tension and multidirectional loading may gradually modify uplift resistance and rotational behavior. This has motivated growing interest in temporal surrogate models that describe how response evolves with loading history rather than treating the resistance envelope as static.

Other deep-water anchoring systems face related difficulties. Plate anchors, helical anchors, and dynamically installed anchors may all be affected by long-term cyclic loading, although the literature remains more limited than for monopiles, suction caisson foundations, and suction anchors. At the system level, the problem becomes broader in multiline mooring systems, where local anchor degradation, line dynamics, and environmental forcing evolve together over time ^[134,135]. From this perspective, one of the main advantages of AI is not simply faster prediction of instantaneous response, but the ability to learn temporal patterns from repeated loading histories and monitoring-informed updates.

3.2.3 Reliability-based design, inverse analysis, and optimization

Once efficient mappings between input parameters and foundation response are available, AI can support design tasks beyond forward prediction, especially reliability analysis, inverse analysis, and optimization. In these applications, response prediction becomes part of a broader

workflow for uncertainty propagation, repeated model evaluations, and design updating (Fig. 7c).

For reliability analysis, traditional random finite-element methods (RFEM) become computationally expensive when soil spatial variability and parameter uncertainty are included explicitly. Surrogate-based frameworks have therefore become increasingly important for failure-probability estimation. Kriging, polynomial chaos expansion (PCE), CNN-based approximations, and related surrogates have been combined with subset simulation and similar sampling techniques to reduce cost [16,22,136–138]. Similar approaches have also been used for probabilistic failure envelopes of suction caisson foundations and suction anchors, as well as for system-level assessment of multiline mooring systems [137–140].

The same idea extends to inverse analysis and optimization. Once the relationship between soil conditions, foundation geometry, loading, and response can be evaluated efficiently, learned surrogates can estimate objectives or constraints while optimization algorithms search the design space. A representative application is ANN-assisted PSO design of offshore wind turbine jackets, where the surrogate estimates structural utilization during initial-population generation [141].

3.2.4 Engineering practice and industrial certification

The role of AI in offshore wind foundation design is gradually shifting from exploratory research toward embedded engineering support. International design consultancies and offshore engineering firms have begun to incorporate surrogate modeling, deep learning, and automated model-generation methods into workflows that support parameter studies and design iteration, reduce repeated use of high-fidelity simulations, and automate geometry generation [142–147]. Examples include Wood Thilsted's Morpheus framework, COWI's COPCAT and COPILOD tools, and related DNV-led initiatives on AI-enhanced engineering workflows [145].

Even so, improved computational efficiency does not automatically translate into

engineering acceptance. Purely data-driven models often provide limited transparency in their internal decision paths and insufficient traceability in mechanical terms, which makes them difficult to use directly in third-party certification. For this reason, organizations such as DNV have begun to establish assurance frameworks for industrial AI applications, drawing on standards such as ISO/IEC 42001 and DNV-RP-0671 ^[148]. This indicates that the industrial uptake of AI in foundation design will depend not only on predictive performance and speed, but also on whether models can be validated, audited, and integrated into established engineering governance procedures.

3.2.5 AI model training and evaluation in foundation design

Table 5 extends the task-based comparison to 163 foundation-design studies. It summarizes their training sources, performance metrics and reported values, and validation methods. The resulting comparison reveals two clear patterns in the available evidence.

The first pattern shows that high reported R^2 values occurred mainly with simulation-based training and evaluation within the source data. Numerical simulations provided the primary training data in 95 studies (58.3%). Among the 85 studies reporting R^2 , 76 (89.4%) reported representative values of at least 0.90. However, 81 of these studies (95.3%) either tested their models on held-out samples from the same data source or used internal or insufficiently described evaluation. Compared with field or physical tests, numerical simulations can generate samples more easily across a wide range of soil, foundation, and loading conditions. The resulting database can then be divided for training and testing without collecting independent project data. These practical advantages may explain both the common use of this approach and the high R^2 values reported. In this setting, R^2 shows how closely a surrogate reproduces the relationships defined by its source numerical model. The surrogate also carries forward the assumptions and errors of that model. Consequently, a high R^2 within the source data provides limited evidence of

performance for field behavior or a new design domain. These models remain useful for repeated calculations and option screening within the validated domain. Independent numerical models, physical tests, and field projects are needed to evaluate their use beyond that domain.

The second pattern is the concentration of both research effort and reported metrics in forward response prediction. Capacity and load-response prediction accounted for 110 studies (67.5%), compared with 30 (18.4%) on cyclic, dynamic, or time-dependent response and 23 (14.1%) on reliability, inverse analysis, or optimization. Parametric simulations can generate forward-response targets in large batches across many design conditions. By comparison, cyclic response requires complete loading histories, while reliability and optimization require rare-event or decision-level outputs. This difference may explain why tasks with readily generated targets dominate the evidence base. It also indicates that data availability and ease of evaluation shape the research agenda alongside engineering importance. Among the 23 reliability, inverse-analysis, and optimization studies, eight reported R^2 and seven reported RMSE, while only two reported relative failure-probability error. Most evaluations therefore focused on how accurately the surrogate reproduced response values. Task-level outcomes, such as accumulated response, failure probability, or constraint satisfaction, were evaluated less often. Future studies should combine standard regression metrics with task-specific measures of cumulative response, failure probability, and constraint satisfaction.

Table 5. Training sources, reported performance, and validation across foundation-design tasks.

Engineering task	Studies, n (%)	Training sources, n (%)	Reported metrics, n (%)	Comparable R^2	Validation profile, n (%)
Capacity and load-response prediction	110 (67.5)	Simulation: 57 (51.8); field: 7 (6.4);	R^2 : 61 (55.5); RMSE: 58 (52.7); MAE:	R^2 , simulation: 0.400–1.000 (n = 37); field: 0.020–	Same-source holdout: 82 (74.5); other external: 7 (6.4); field

Engineering task	Studies, n (%)	Training sources, n (%)	Reported metrics, n (%)	Comparable R^2	Validation profile, n (%)
		other: 46 (41.8)	38 (34.5); MAPE: 21 (19.1)	0.950 ($n = 3$); other: 0.260–1.000 ($n = 21$)	case: 3 (2.7); CV: 4 (3.6); internal/unclear: 14 (12.7)
Cyclic, dynamic, and time-dependent response	30 (18.4)	Simulation: 19 (63.3); field: 1 (3.3); other: 10 (33.3)	R^2 : 16 (53.3); RMSE: 12 (40.0); MAE: 7 (23.3)	R^2 , simulation: 0.660–1.000 ($n = 11$); other: 0.160–0.991 ($n = 5$)	Same-source holdout: 20 (66.7); other external: 2 (6.7); internal/unclear: 8 (26.7)
Reliability, inverse analysis, and optimization	23 (14.1)	Simulation: 19 (82.6); field: 3 (13.0); other: 1 (4.3)	R^2 : 8 (34.8); RMSE: 7 (30.4); relative failure-probability error: 2 (8.7)	R^2 , simulation: 0.889–0.998 ($n = 8$)	Same-source holdout: 11 (47.8); other external: 2 (8.7); CV: 1 (4.3); internal/unclear: 9 (39.1)

Note: n : number of unique studies. Task count: one dominant engineering task per study. Metric count: non-exclusive; one study may report multiple metrics. Comparable performance: range of study-level representative R^2 values at the highest available evaluation level. Other training sources: laboratory data ($n = 24$); hybrid/mixed data ($n = 17$); secondary/public databases ($n = 15$); synthetic/analytical data ($n = 1$). CV: cross-validation. MAE: mean absolute error. MAPE: mean absolute percentage error. RMSE: root mean square error. Detailed results: Supplementary Table S3.

3.3 Foundation Installation

Offshore foundation installation involves a dynamic balance between penetration resistance and the applied driving force, such as hammer impact, internal suction, or ballast loading^[149]. For large-diameter monopiles, prediction errors may lead to pile running or refusal during installation^[77]. For jack-up spudcans, similar uncertainty in penetration resistance may trigger sudden punch-through in layered soils^[150]. For suction caisson foundations and suction anchors, the installation process is further complicated by suction-assisted penetration, under which plug blockage, buckling, and piping may occur^[151].

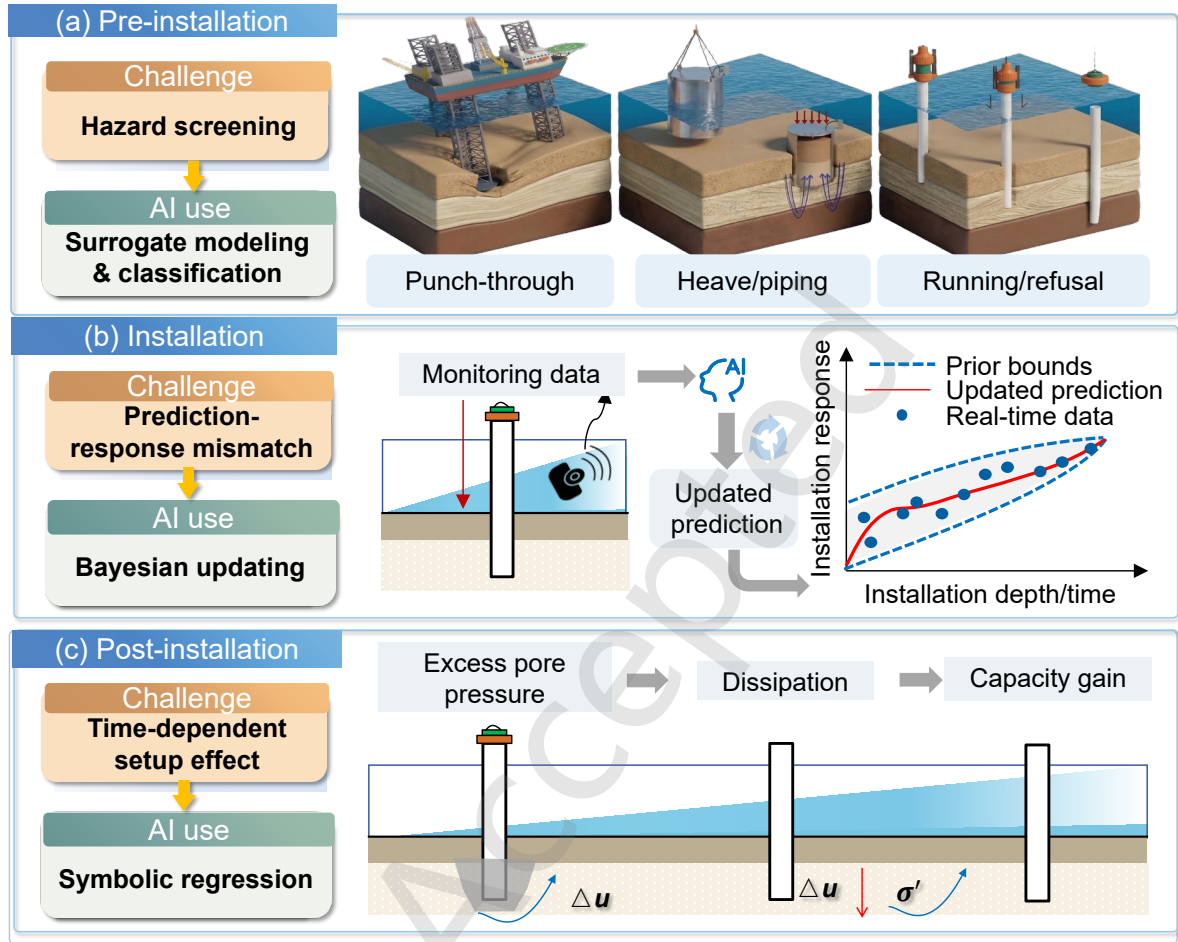


Fig. 8. AI-assisted technical routes across three phases of offshore foundation installation. (a) Pre-installation hazard screening using surrogate modeling and classification, illustrated by punch-through, heave/piping, and running/refusal. (b) Bayesian updating of predicted installation response using real-time monitoring data. (c) Symbolic regression to model post-installation setup as excess pore-water pressure dissipates and foundation capacity increases ^[152–154]. Δu , excess pore-water pressure; σ' , effective stress.

These processes involve large deformation, evolving contact conditions, rapid pore-pressure changes, and, in some cases, strain-rate or seepage effects ^[155–157]. Conventional installation analysis therefore faces a persistent trade-off between efficiency and fidelity. One-dimensional wave-equation methods and API-based static reduction approaches are computationally efficient, but rely heavily on empirical parameter selection and may perform poorly when resistance changes abruptly in

layered ground ^[158]. By contrast, large-deformation numerical methods, especially coupled Eulerian–Lagrangian (CEL) approaches, have been used to simulate offshore foundation penetration and the associated soil-flow mechanisms ^[159–161]. These methods provide detailed mechanistic information but are generally used for offline analyses, making them less suited to rapid updates during field operations. In this context, AI is increasingly used for pre-installation feasibility assessment, real-time monitoring and correction during installation, and post-installation back-analysis (Fig. 8).

3.3.1 Installation feasibility assessment and rapid risk prediction

At the planning stage, the main objective is to estimate penetration resistance and identify potential installation hazards before construction begins. Because site data are often still limited, AI is mainly used to build efficient surrogate models that reduce repeated use of time-consuming physical simulations and enable rapid feasibility screening.

One central task is the prediction of soil resistance to driving (SRD), for which traditional wave-equation-based workflows are sensitive to soil parameter selection. Park and Cho ^[152] showed that artificial neural networks (ANNs) could establish nonlinear relationships among hammer energy, soil conditions, and penetration resistance more effectively than wave-equation approaches. For foundation types with more complex penetration mechanisms (e.g., helical piles and dynamically installed anchors), multivariate machine-learning models have been used to predict installation torque and final embedment depth, where analytical methods struggle to represent the full 3D process ^[154,162].

Machine learning has also been used to identify pre-installation risks. For plugging issues for large-diameter pipe piles, research has progressed from qualitative judgment to probabilistic prediction using ensemble voting classifiers based on foundation geometry and bulk soil indices ^[163,164]. For internal plug heave that often occurs during suction-assisted penetration, recent studies suggest that ensemble-

learning methods, such as random forest regression (RFR), can combine installation parameters with stratigraphic indicators to predict plug-heave height more reliably than conventional empirical correlations ^[165]. For spudcan punch-through in layered soils, surrogate models based on random forest (RF) and multilayer perceptron (MLP), trained on CEL-generated samples, have been used to improve efficiency and support the development of site-scale punch-through vulnerability maps ^[166–168].

3.3.2 Real-time monitoring and adaptive updating during installation

During installation, discrepancies often arise between pre-installation predictions and measured field response due to seabed heterogeneity and limited site investigations. At this stage, the main contribution of AI lies in using high-frequency monitoring data to update soil resistance and installation response in real time.

For impact-driven foundations such as monopiles, interpretation of driving response still depends largely on wave-equation analysis, whose reliability is strongly influenced by assumed pile-soil interaction parameters. Since these parameters are difficult to define reliably in advance, probabilistic approaches such as Bayesian updating have been used to revise empirical parameters, including Smith damping and ultimate elastic displacement, using hammer-response time histories recorded during early driving ^[169,170]. This reduces prediction error in deeper penetration stages. For pile-running risk in weak layers ^[77], deep-learning-based temporal models have also been used to detect precursory instability from monitoring signals, while attribution tools (e.g., SHAP) help quantify the contribution of variables such as mudline elevation and hammer energy ^[171].

During suction-assisted installation, a key challenge is real-time control of the suction path. If suction is too low, penetration is insufficient; if it is too high, piping or excessive plug heave may occur ^[172]. In this setting, data assimilation has been used to infer effective wall stress and critical suction path from early displacement and pressure measurements, thereby informing pump-pressure control ^[173]. For concealed

risks associated with non-uniform plug heave and premature internal contact, intelligent spatial interpolation has also been used to guide adaptive sonar sounding and reconstruct 3D plug geometry with limited sampling delay ^[174].

Similar benefits have been reported for jack-up spudcans. Bayesian inference can progressively narrow the posterior uncertainty in peak penetration resistance and uplift capacity as monitoring data accumulate ^[175–177]. For strongly nonlinear processes involving coupled interface friction and large soil deformation, higher-order state-estimation methods such as the ensemble Kalman filter (EnKF) and particle filter have been used to track the evolution of end-bearing and shaft-resistance components under noisy conditions ^[178,179]. In this sense, installation is increasingly treated as a form of in-situ testing, with site investigation and construction becoming more tightly linked.

3.3.3 Post-installation setup and back-analysis

After pile driving or suction penetration, the disturbed soil around the foundation undergoes pore-pressure dissipation and thixotropic strength recovery, commonly referred to as the setup effect. This process affects the initial post-installation capacity and is therefore relevant to later performance reassessment. Traditional empirical approaches usually describe setup using logarithmic time functions, but these formulations are often too simple to capture nonlinear asymptotic recovery at later times.

For such strongly time-dependent behavior, symbolic-regression-based evolutionary methods, especially gene expression programming (GEP), have shown potential for deriving explicit relationships among recovered capacity, consolidation time, fines content, and geometric parameters ^[180,181]. Compared with black-box neural networks ^[182], these expressions are easier to interpret and more convenient for rapid estimation and design checking. However, this line of work remains relatively limited, and its current role is mainly to support post-installation reassessment rather than real-time installation control.

3.3.4 Engineering practice and equipment digitalization

In recent years, offshore contractors have increasingly incorporated simulation and digital technologies into foundation-installation workflows. One documented example is Jan De Nul's use of digital-twin installation simulators to rehearse offshore wind turbine and foundation operations under changing sea and seabed conditions ^[183].

At the operational level, Heerema, Boskalis, and Saipem are combining high-fidelity simulation with digital-twin technology to update motion and load response during offshore installation, improving lowering, positioning, and alignment control ^[184–186]. In penetration monitoring, tools such as those developed by G-Octopus are also being used to infer pile-tip resistance and possible boulder occurrence from stress-wave signals ^[187].

At the equipment level, installation systems are moving from manual open-loop operation toward adaptive control based on soil–machine feedback. In next-generation hydraulic hammer systems developed by IHC IQIP, integrated sensors and optimization algorithms can adjust hammer energy or operating frequency in real time when abnormal pile–soil interaction is detected ^[188].

These developments suggest that the value of intelligent installation is shifting from prediction alone toward active construction control and equipment capability enhancement.

3.3.5 AI model training and evaluation in foundation installation

Table 6 compares training sources, reported metrics and values, and validation methods across 20 foundation-installation studies.

First, installation studies relied more on measured data and existing databases than on simulation-generated datasets. Numerical simulation was the primary training source in only two studies (10.0%), compared with 58.3% of foundation-design studies. Seven installation studies used laboratory data, seven used secondary or public databases, three used field data, and one used hybrid data. This distribution is

consistent with the greater difficulty of modeling installation processes. Compared with conventional capacity calculations, installation models must represent large deformation, evolving contact, soil flow, and changes in pore pressure and seepage. These requirements make reliable numerical samples more difficult to generate and calibrate, which may explain the greater reliance on experiments and existing records.

The same data constraints also shaped the distribution of installation objects. Among the 11 studies on penetration and installation response, six examined spudcans, two examined piles, two examined suction caissons, and one examined a Hall anchor. Spudcan penetration can be reproduced in controlled centrifuge tests under layered-soil conditions, with clear targets such as peak resistance and penetration depth. By contrast, most pile studies in the broader installation set focused on post-installation capacity gain or plugging rather than the complete driving process. This concentration suggests that data accessibility, rather than engineering importance alone, has influenced the current research focus. Complete pile-driving and suction-caisson penetration processes therefore remain underrepresented in the included evidence.

Second, installation studies have begun to use monitoring data to update predictions of later resistance, punch-through risk, or critical suction. However, the available evaluations compared predictions with observations, and none of the 20 studies assessed a complete monitoring–update–control–feedback loop. Current evidence therefore supports AI for monitoring and decision support, while closed-loop control still requires prospective field validation of its effectiveness and safety.

Table 6. Training sources, reported performance, and validation across foundation-installation tasks.

Engineering task	Studies, <i>n</i> (%)	Training sources, <i>n</i> (%)	Reported metrics, <i>n</i> (%)	Comparable performance	Validation profile, <i>n</i> (%)
Penetration and installation-	11 (55.0)	Simulation: 2 (18.2); field: 2	R^2 : 6 (54.5); RMSE: 4 (36.4);	R^2 , simulation: 0.973–0.997 (n = 2); field: 0.800–	Same-source holdout: 8 (72.7);

Engineering task	Studies, <i>n</i> (%)	Training sources, <i>n</i> (%)	Reported metrics, <i>n</i> (%)	Comparable performance	Validation profile, <i>n</i> (%)
response prediction		(18.2); other: 7 (63.6)	MAE: 4 (36.4)	0.830 (<i>n</i> = 2); other: 0.444–0.980 (<i>n</i> = 2)	internal/unclear: 3 (27.3)
Hazard/state classification and updating	4 (20.0)	Field: 1 (25.0); other: 3 (75.0)	Accuracy: 3 (75.0); relative error: 1 (25.0)	Accuracy, field: 0.890 (<i>n</i> = 1); other: 0.710 (<i>n</i> = 2)	Cross-validation: 1 (25.0); other external: 2 (50.0); internal/unclear: 1 (25.0)
Post-installation setup and capacity evolution	5 (25.0)	Other: 5 (100.0)	R^2 : 4 (80.0); RMSE: 5 (100.0); MAE: 2 (40.0)	R^2 , other: 0.730–0.950 (<i>n</i> = 4)	Same-source holdout: 3 (60.0); other external: 1 (20.0); internal/unclear: 1 (20.0)

Note: *n*: number of unique studies. Task allocation: one dominant engineering task per study. Metric counts: non-exclusive. Comparable performance: range of study-level representative values at the highest available evaluation level. Other training sources: laboratory data (*n* = 7); secondary/public databases (*n* = 7); hybrid/mixed data (*n* = 1). Same-source holdout: test samples drawn from the same underlying source as the training data. Other external: evaluation using an independent dataset other than a field-case assessment. Setup: installation-induced capacity gain over time. MAE: mean absolute error. RMSE: root mean square error. Detailed results: Supplementary Table S4.

3.4 Operation and Maintenance (O&M)

After installation, offshore wind foundations continue to evolve under long-term environmental loading. Unlike superstructures, geotechnical problems such as seabed scour and degradation of structure-soil interaction (SSI) mainly occur below water (or below mudline) and are therefore difficult to observe directly. These processes are both cumulative and potentially abrupt: gradual scour and stiffness degradation may progress over time ^[189,190], while subsequent extreme events can trigger sudden failures once a critical state is reached ^[191]. Conventional O&M still relies largely on periodic sonar surveys or diver inspection, both of which are costly, infrequent, and inherently delayed ^[13].

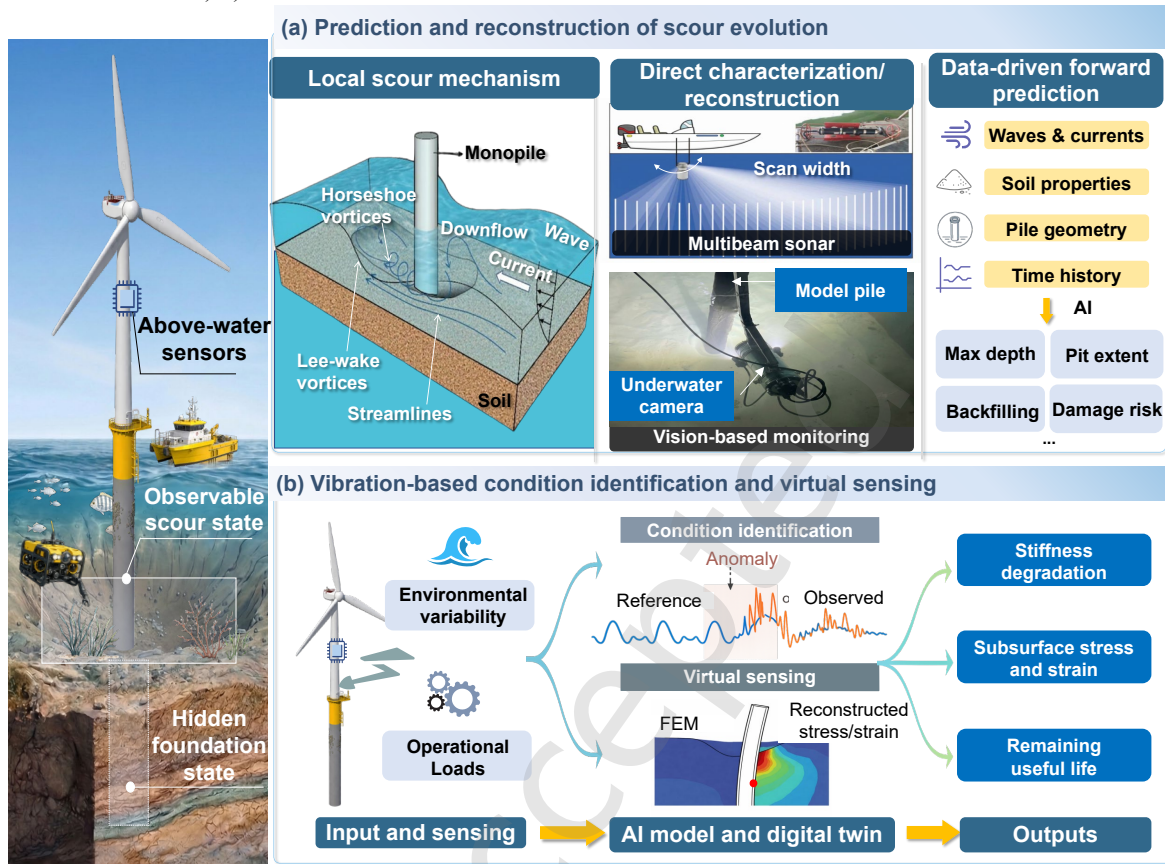


Fig. 9. AI-assisted routes for offshore geotechnical operation and maintenance (O&M). The left schematic contrasts scour that can be characterized through underwater observation with below-mudline foundation states that require indirect inference. (a) Scour assessment through representation of local mechanisms (modified from ^[192]), direct characterization and reconstruction using data from multibeam sonar and underwater cameras (modified from ^[193,194]), and data-driven forward prediction. (b) Vibration-based condition identification and virtual sensing, linking above-water measurements to anomaly detection, reconstruction of subsurface stress and strain, stiffness degradation, and remaining useful life. AI, artificial intelligence; FEM, finite-element model.

Against this background, AI and digital-twin technologies are shifting this paradigm toward predictive, data-driven risk management. Current work mainly concentrates on three aspects: (1) prediction and reconstruction of scour evolution, (2) vibration-based condition identification and virtual sensing for hidden foundation response, and (3) closed-loop O&M enabled by intelligent monitoring and digital updating. The first two technical routes are summarized schematically in **Fig. 9**.

3.4.1 Prediction and reconstruction of scour evolution

Local scour around monopiles arises from complex fluid-soil interactions involving horseshoe vortices, wake shedding, and the associated amplification of near-bed shear stress [195]. Conventional empirical equations, mostly derived from simplified flume tests, often struggle to capture site-specific wave-current loading and boundary-layer processes [196,197].

In this context, AI enhances scour assessment mainly through two complementary routes (**Fig. 9a**). The first focuses on direct characterization and reconstruction of scour morphology from monitoring data. Compared with infrequent manual interpretation, AI-enhanced analysis transforms multibeam-sonar data and underwater imagery into engineering-relevant scour indicators and reconstructed pit geometry under visually challenging underwater conditions, enabling automatic scour-pit detection [198,199], deepest-point localization, geometric quantification, and 3D site reconstruction, thereby improving the timeliness and consistency of field assessment [193,194,200].

The second route focuses on data-driven forward prediction of scour evolution under changing environmental forcing. Learning-based models relate hydrodynamic and environmental parameters to engineering-relevant scour metrics. For example, ensemble-learning methods have been applied to quantify the nonlinear influence of key parameters (e.g., Keulegan-Carpenter number and Shields parameter) on scour depth [201,202]. In practice, however, deep-water in-situ data are often sparse, so the limited field observations are commonly combined with high-fidelity numerical simulations to improve model robustness [203]. Additionally, scour prediction is moving from deterministic estimates (i.e., point prediction) toward probabilistic forecasts for O&M reliability assessment (e.g., spatio-temporal reconstruction) [204], using sequence models for time-dependent evolution under changing sea states [205–208] and graph neural networks (GNNs) for inference at unmonitored locations across a wind farm [198,209,210].

3.4.2 Vibration-based condition identification and virtual sensing

Compared with scour, degradation below the mudline is even harder to observe directly, although it can still alter foundation stiffness and boundary restraint. A practical alternative is to infer foundation-condition change from vibration measured above water. Such interpretation usually proceeds at two levels: (1) condition identification and (2) virtual sensing for hidden-response reconstruction (**Fig. 9b**).

The first level detects changes in foundation state from vibration features such as natural frequency, mode shape, and time-frequency indicators ^[211,212]. In offshore wind applications, however, environmental and operational variability, sparse labels, and mixed damage sources make this task difficult. AI is mainly used to improve feature extraction and pattern discrimination. Some studies embed structural-dynamics constraints directly into the loss function so that scour depth or stiffness degradation can be inferred from limited vibration data ^[213]. Others use anomaly detection based on healthy-state baselines to identify departures from normal behavior without a complete fault library ^[214]. Vibration-based studies address scour identification ^[215,216], combined scour and structural damage ^[217], and damage identification in soil-supported monopile systems ^[218]. At this stage, the result is still mainly a system-level indication of foundation change, but it is already useful for anomaly screening, condition tracking, and early warning.

The second level recovers the below-mudline response history needed for quantitative assessment. For service-life evaluation, identifying a stiffness change is not enough; the key requirement is the stress–strain or response history in critical structural or soil regions below the mudline. This is difficult when loads are unmeasured, monitoring is sparse, and SSI is strongly nonlinear. AI is increasingly used in digital-twin-based inverse analysis to address this problem. One approach jointly estimates external loading and structural response when direct load measurements are unavailable ^[219,220]. Another introduces latent-variable dynamic

models to represent nonlinear hysteresis and reconstruct hidden subsurface states from limited observations ^[221]. More generally, AI supports high-dimensional inverse mapping and latent state updating under incomplete observations ^[219,220]. This pushes vibration-based interpretation beyond anomaly indication toward quantitative reconstruction of below-mudline response, providing a more direct basis for fatigue analysis and service-life evaluation.

3.4.3 Reliability updating and prognosis

Once scour state or below-mudline response can be inferred with greater confidence, the next step is long-term performance assessment. Conventional fatigue and reliability frameworks remain essential, but repeated updating becomes computationally burdensome when loading and multiple degradation mechanisms evolve over long service periods ^[222,223]. AI is mainly used here to improve uncertainty propagation, surrogate-based updating, and data-informed reliability tracking.

Recent studies combine reliability analysis with Copula-based descriptions of environmental dependence and random-field representations of spatially variable soil properties, while using active-learning surrogates such as sequential Kriging or Gaussian-process models to reduce repeated calls to expensive simulations ^[224–226]. These workflows make it more feasible to track reliability evolution under combined scour, corrosion, and geotechnical degradation, and to incorporate sparse monitoring data into fatigue assessment, reliability updating, and life-extension analysis. In this sense, AI is extending offshore geotechnical O&M from condition identification toward prognosis by making long-term updating more practical.

3.4.4 Engineering practice and closed-loop O&M support

The purpose of intelligent monitoring is to connect data acquisition, condition identification, risk assessment, and maintenance actions into a workable O&M loop. In practice, this is becoming visible in three areas: unmanned scour inspection, automated confined-space monitoring, and digital-twin-supported life-extension assessment.

In scour and seabed-morphology monitoring, practice is shifting from vessel- and diver-based inspection toward AI-supported unmanned surveying and 3D quantification. Fugro, for example, has applied unmanned surface vehicle (USV)-based remote survey systems for offshore wind foundations and cable-protection inspection ^[227,228], while Beam has also demonstrated autonomous subsea inspection with on-site 3D reconstruction. These developments make scour monitoring more frequent, quantitative, and less dependent on offshore personnel ^[229].

For monopile shafts and other confined spaces, inspection is also becoming more automated. Ørsted's Confispace solution combines drones with AI-based image analysis to reduce personnel exposure and inspection effort ^[230]. At the same time, SCADA- and sensor-based predictive monitoring is increasingly used to track degradation trends and support preventive maintenance in turbines and substations ^[230].

In life-extension assessment, attention is shifting from isolated sensing to integrated digital-twin systems. Acteon has applied this approach in floating offshore wind demonstrators, using measured motion, position, and strain data to update structural-response twins and infer loading and deformation in inaccessible underwater regions ^[231–233]. These developments show that intelligent monitoring is moving beyond periodic inspection and post-processing toward more continuous closed-loop O&M support.

3.4.5 AI model training and evaluation in operation and maintenance

Table 7 compares training sources, reported metrics and values, and validation methods across 35 O&M studies.

First, although O&M is grounded in field monitoring, most included studies did not train their models directly on measurements from operating assets. Within the assembled evidence set, none of the 14 scour studies or 12 condition-identification and prognosis studies used directly collected operational data as the primary training

source. Scour studies relied mainly on numerical simulations, laboratory data, and existing databases. Condition studies used either numerical simulations ($n = 7$) or laboratory data ($n = 5$). Among these 26 studies, ten reported R^2 , with study-level representative values ranging from 0.590 to 1.000. These results were obtained from simulations, laboratory tests, or existing databases rather than directly collected operational data. Scour assessment requires long-term records that align environmental loading with seabed evolution, while condition identification requires verified damage or degradation labels. Both types of evidence are difficult to obtain from operating assets. Simulations and controlled tests provide clearer target states, which may explain their dominant role in current model development.

Second, field data were concentrated in hidden-response reconstruction and model updating, but measured inputs did not necessarily provide reference values for the predicted states. Five of the nine studies in this task group used field data, and all five relied on internal or insufficiently described evaluation. Below-mudline strain, foundation stiffness, and external loads often cannot be measured directly. Some studies therefore used the modal assurance criterion or correlation coefficients to evaluate reconstructed responses. However, agreement with above-water structural responses or an updated numerical model does not independently verify the reconstructed below-mudline state. Current evidence therefore supports AI for virtual sensing and model updating, while its use in maintenance decisions still requires validation against independent inspection results or subsequent operating data.

Table 7. Training sources, reported performance, and validation across operation-and-maintenance tasks.

Engineering task	Studies, n (%)	Training sources, n (%)	Reported metrics, n (%)	Comparable performance	Validation profile, n (%)
Scour prediction and detection	14 (40.0)	Simulation: 5 (35.7); field:	R^2 : 5 (35.7); RMSE: 10	R^2 , simulation: 0.885–0.995 ($n =$	Same-source holdout: 10 (71.4); other external: 1

Engineering task	Studies, <i>n</i> (%)	Training sources, <i>n</i> (%)	Reported metrics, <i>n</i> (%)	Comparable performance	Validation profile, <i>n</i> (%)
		0; other: 9 (64.3)	(71.4); MAE: 6 (42.9)	1); other: 0.590–0.942 (<i>n</i> = 4)	(7.1); cross-validation: 1 (7.1); internal/unclear: 2 (14.3)
Condition identification and prognosis	12 (34.3)	Simulation: 7 (58.3); field: 0; other: 5 (41.7)	R^2 : 5 (41.7); accuracy: 2 (16.7); precision: 3 (25.0); F1: 1 (8.3)	R^2 , simulation: 0.910–1.000 (<i>n</i> = 3); other: 0.918–0.998 (<i>n</i> = 2); accuracy, other: 0.940–0.999 (<i>n</i> = 2)	Same-source holdout: 7 (58.3); other external: 1 (8.3); cross-validation: 2 (16.7); internal/unclear: 2 (16.7)
Hidden-response reconstruction and model updating	9 (25.7)	Simulation: 3 (33.3); field: 5 (55.6); other: 1 (11.1)	Normalized RMSE: 3 (33.3); MAC: 2 (22.2); correlation coefficient: 1 (11.1)	Normalized RMSE, simulation: 0.3–80% (<i>n</i> = 2); other: 1.4% (<i>n</i> = 1); MAC, field: 0.870–0.999 (<i>n</i> = 2); correlation, field: 0.968 (<i>n</i> = 1)	Same-source holdout: 1 (11.1); other external: 1 (11.1); internal/unclear: 7 (77.8)

Note: *n*: number of unique studies. Task allocation: one dominant engineering task per study. Metric counts: non-exclusive. Field training: directly collected measurements from operating assets. Other training sources: laboratory data (*n* = 8); secondary/public databases (*n* = 5); hybrid/mixed data (*n* = 2). Comparable performance: range of study-level representative values at the highest available evaluation level. Same-source holdout: test samples drawn from the same underlying source as the training data. Other external: evaluation using an independent dataset other than a field-case assessment. MAC: modal assurance criterion. MAE: mean absolute error. RMSE: root mean square error. Detailed results: Supplementary Table S5.

3.5 Cross-lifecycle synthesis

Sections 3.1–3.4 reviewed the AI research tasks, technical approaches, and engineering practice at each lifecycle stage. Tables 4–7 further compared how the models were trained and evaluated. Technical studies show which tasks AI has been used to perform, while documented project cases indicate whether these methods have entered engineering workflows. The quantitative results show which data underpin the reported performance and how that

performance was evaluated. Taken as a whole, these analyses yield three cross-lifecycle findings.

(1) Use in an engineering workflow does not by itself establish independent validation. Here, independent validation means testing a model on a site, project, or design or operating condition that was not used in model development. In site investigation, AI-generated digital ground models have been used in tenders and as design inputs, but transfer to new sites has rarely been tested. Foundation-design surrogates are already used in parametric studies and design iteration, although most reported results show how closely they reproduce the numerical simulations used for training. Documented project cases thus demonstrate workflow adoption, but do not alone establish transferability or readiness for independent engineering decisions.

(2) AI is closest to step-level substitution when the task is bounded and its output can be checked before the final engineering decision. Representative examples are within-site data processing during site investigation, surrogate calculations within a validated foundation-design domain, and observable-condition identification from images or sonar in O&M. Measured profiles, separate high-fidelity calculations, and inspection results provide the corresponding checks. The reviewed evidence therefore supports selective substitution for some data-processing and repeated-calculation steps. Direct site investigation, complete design verification, and final engineering review remain within established workflows.

(3) Stronger evidence is required when AI outputs inform construction, maintenance, or certification decisions. Installation studies have used monitoring data to update penetration-resistance and risk predictions, but none of the reviewed studies assessed the complete chain from prediction and equipment adjustment to the final construction outcome. Many below-mudline O&M states lack direct reference measurements. Similarly, high agreement with source simulations does not provide the traceability required for certification-level design. These decision-level uses

therefore require established analysis, field verification, and expert judgment alongside AI.

Table 8 applies these three findings across the four lifecycle stages.

Table 8. Current AI roles and evidence boundaries across the offshore wind geotechnical lifecycle.

Lifecycle stage	Reported applications and available engineering evidence	Role relative to established methods	Current evidence boundary
Site investigation	AI is used for CPT interpretation, seismic–CPT fusion, and digital ground modeling; some outputs have been used in tenders and as design inputs	Selective substitution and supplementation: performs some within-site data processing and parameter prediction while supplementing direct investigation and expert interpretation	The reviewed evidence does not support replacement of boreholes or CPTs; cross-site transfer remains insufficiently validated
Foundation design	Surrogates are used for response prediction, parametric studies, design iteration, and option screening	Selective substitution and supplementation: handles some repeated numerical evaluations within a validated design domain and supplements mechanical analysis and code-based design	Conditions outside the training domain and certification-level design still require independent verification
Foundation installation	AI has been applied to installation-risk prediction and monitoring-based updates; digital monitoring systems provide an implementation basis for these applications	Supplementation: assists feasibility assessment, hazard identification, and prediction updating	No reviewed study directly evaluated whether AI-guided closed-loop control safely improves construction outcomes
O&M	AI-based image and sonar analyses identify observable conditions; virtual sensing supports hidden-response reconstruction and model updating	Selective substitution and supplementation: handles some routine inspection-data processing and supplements state inference and reliability updating	Hidden-state inference and decisions on maintenance or life extension still require independent evidence

Note: Selective substitution: AI performs a bounded step whose output can be independently checked; established engineering review remains in the workflow.

Overall, the extent of AI use depends on the task rather than the lifecycle stage.

Step-level substitution is clearest for surrogate calculations within validated foundation-design domains. Site investigation and O&M approach this level only for observable, checkable outputs, whereas foundation installation remains focused on prediction and decision support. The evidence base is strongest for reproducing established calculations and identifying observable conditions, but weaker for hidden-state inference, real-time control, and certification. Accordingly, AI can currently replace selected calculations and data-processing steps; direct site characterization, final verification, and responsibility for engineering decisions remain within established workflows. Section 4 examines the data, model, transferability, and implementation barriers that underlie these boundaries.

4 Key Challenges and Limitations

Recent reviews and application studies in civil and geotechnical engineering suggest that, despite differences in application context, the main barriers to practical AI implementation are broadly similar. Based on 12 representative between 2020 and 2025 [8,15,24,234–242], rather than on the 266 screened research articles, the challenges can be broadly grouped into four categories: data-related limitations, model-related limitations, generalization limitations, and implementation-related limitations (**Fig. 10**). At the category level, data- and model-related limitations account for the largest shares, followed by generalization- and implementation-related limitations. At the level of specific issues, the six most frequently reported limitations are data scarcity (100%), limited interpretability (91.7%), insufficient generalization (83.3%), data-quality concerns (75%), limited engineering deployment (75%), and lack of standardization (66.7%). When considered together with the stage-based analysis in Section 3, these findings suggest that AI in offshore geotechnical engineering is constrained not by a single weakness, but by a chain of interrelated limitations spanning data, models, transferability, and deployment.

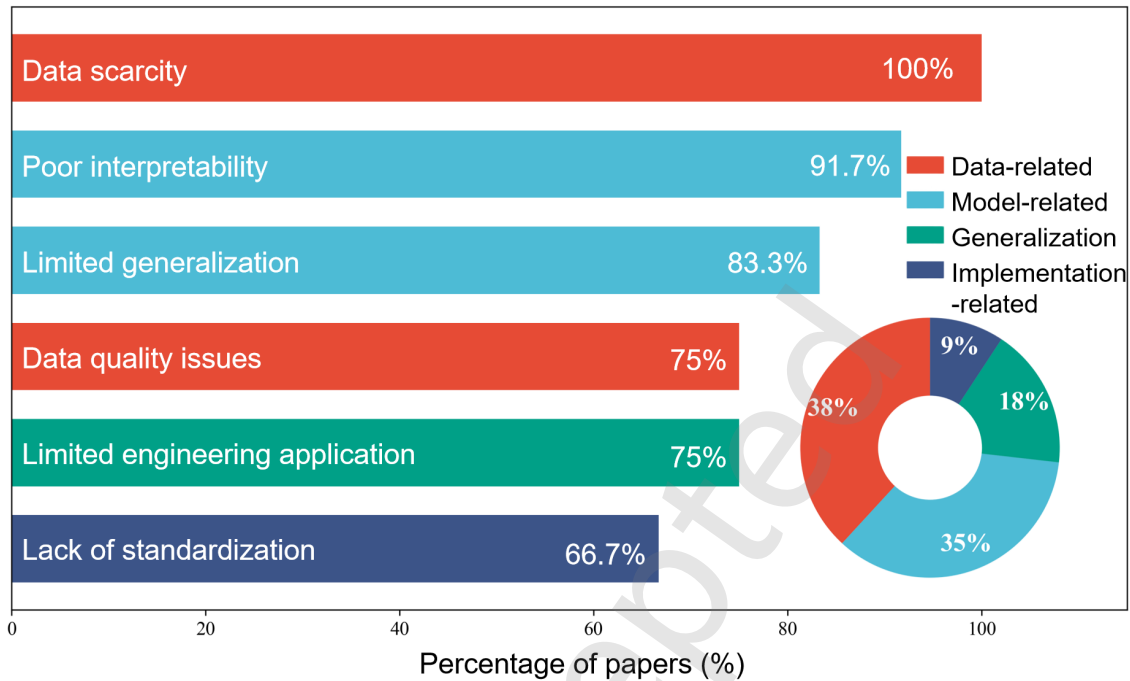


Fig. 10. Summary of key barriers to AI implementation in geotechnical engineering. Bar chart: frequency of specific limitations; Donut chart: proportional distribution by limitation category (Data-related, Model-related, Generalization, and Implementation-related).

4.1 Data scarcity and insufficient quality control

The most immediate limitation remains the lack of high-quality offshore geotechnical data. Full-scale installation records, deep borehole measurements, and long-term monitoring datasets are expensive and sparse. As a result, many AI models still rely on numerical simulations, smooth interpolations, or limited site-specific observations that do not fully reflect real seabed variability, installation disturbance, or measurement noise under marine conditions. Models trained primarily on synthetic data can therefore lead to biased prediction when transferred to more complex field conditions ^[170,243].

This problem is intensified by inconsistent quality control. Offshore datasets often differ in test protocols, sampling resolution, feature definition, and preprocessing procedures. Missing values, noise, and inconsistent labels further reduce reliability. The lack of shared, reusable benchmark datasets therefore remains a basic obstacle to robust training, fair comparison, and practical credibility.

4.2 Limited physical grounding and interpretability

A second major limitation is that many current models remain weakly connected to geotechnical mechanisms. Although purely data-driven models may fit observed patterns well within the training range, they often rely on statistical association rather than explicit mechanics. As a result, they may produce unrealistic resistance changes, stiffness evolution, or failure trends under unfamiliar conditions.

Interpretability is part of the same problem. In engineering practice, predictions must be explainable and defensible, not only accurate. However, many current models operate as black boxes and provide limited insight into stress transfer, failure evolution, or the mechanical basis of their outputs. This weakens confidence in design, installation, and life-extension decisions.

4.3 Limited generalization across regions, conditions, and time scales

Model transferability remains another major challenge. A model trained in one sea area or for one task may degrade quickly when applied to sites with different depositional histories, soil characteristics, or failure mechanisms ^[244]. This is especially important in offshore wind because foundations operate under long-term coupling among wind, wave, current, and soil, with time-dependent processes such as stiffness degradation and pore-pressure accumulation. As a result, models that fit local static data may still be inadequate for stable long-term extrapolation.

4.4 Implementation barriers and regulatory review challenges

Even when predictive performance is acceptable, deployment in real projects remains difficult. Offshore engineering often involves weak connectivity, limited onboard computing resources, and legacy software environments, which favor lightweight, stable, and low-latency tools. Some current probabilistic and filtering methods are still too computationally demanding for real-time field use ^[179].

At the same time, offshore geotechnical AI still lacks unified standards for data format, feature definition, sample quality control, model validation, and performance

evaluation. This weakens reproducibility, complicates third-party review, and slows integration into certification and engineering practice. Improving predictive accuracy alone is therefore insufficient; reviewability and standardization are equally important.

5 Outlook

The challenges above suggest that future progress should focus less on isolated prediction accuracy gains and more on whether AI models and workflows are physically grounded, transferable, and usable in engineering practice. In this sense, this section responds to the limitations identified in Section 4: trustworthy models address weak physical grounding, interpretability, and generalizability; stronger data ecosystems address data scarcity, inconsistent quality, and industrial deployment barriers; and agent-assisted workflows explore how models, evidence, and engineering tasks can be connected.

5.1 Model reconstruction for trustworthy prediction

To address the problems of insufficient physical grounding, limited interpretability, and limited generalization (Sections 4.2 and 4.3), future model development should place greater emphasis on trustworthy prediction rather than higher accuracy alone. In offshore geotechnics, the key challenge is ensuring AI models remain mechanically plausible when applied beyond the training domain.

One important direction is stronger integration of physical constraints. Existing physics-informed neural networks (PINNs) usually impose physical information through residual terms in the loss function, but this may be insufficient for problems involving large deformation, strong coupling, or pronounced nonlinearity. A more robust route is to embed conservation laws, dissipation conditions, and boundary constraints more explicitly into model structure. Thermodynamics-based artificial neural networks (TANN) are one example of this trend and may offer more reliable physical boundaries for stiffness degradation, plastic dissipation, and strength evolution in offshore geotechnical applications ^[245].

A second direction is improved transparency. In engineering practice, models

must produce outputs that engineers can inspect and relate to approximate mechanisms or design relationships. This has motivated interest in more interpretable architectures, such as Kolmogorov-Arnold networks (KANs) ^[246].

Overall, future model development is likely to rely less on increasing network complexity alone and more on combining physical consistency and interpretability.

5.2 Data ecosystems, benchmark datasets, and standardization

To address the challenges of data scarcity, inconsistent data quality, and engineering deployment barriers (Sections 4.1 and 4.4), offshore geotechnical AI needs stronger data ecosystems, benchmark datasets, and standardized evaluation frameworks. These are essential for improving comparability, reproducibility, and reviewability across studies and projects.

There have been encouraging developments in data accessibility. For example, in the Netherlands, public pre-tender datasets containing CPTu, borehole, and geophysical survey data have become available, and national data platforms now provide broader subsurface records ^[247]. Even so, open data ecosystems designed specifically for offshore geotechnical AI remain at an early stage.

An equally important issue is benchmark design. Without common benchmarks, different studies continue to report performance on self-defined datasets and metrics, making objective comparison difficult. Offshore benchmark frameworks should therefore move beyond predictive accuracy alone and include questions of physical consistency, cross-site stability, and reproducible engineering assessment. Recent benchmark-oriented efforts (e.g., 2025 GEOAI benchmark problem published in *Geodata and AI* ^[248]) indicate growing interest in this direction, but offshore geotechnics still needs coordinated development of open datasets and standardized workflows for quality control, validation, and reporting.

5.3 Agent-assisted engineering workflows

Beyond better models and datasets, agent-assisted workflows offer a longer-term direction for connecting modeling, data analysis, and engineering software. Here, a language-model

agent is an AI system that divides a task into steps, uses approved data or software, and selects its next step from intermediate results [249,250]. When several agents perform different roles, they form a multi-agent system. Building on recent developments in geotechnics and adjacent sciences, we envisage three connected levels for offshore engineering: support for a single modeling task, feedback between models and evidence, and coordination across an engineering project (Fig. 11).

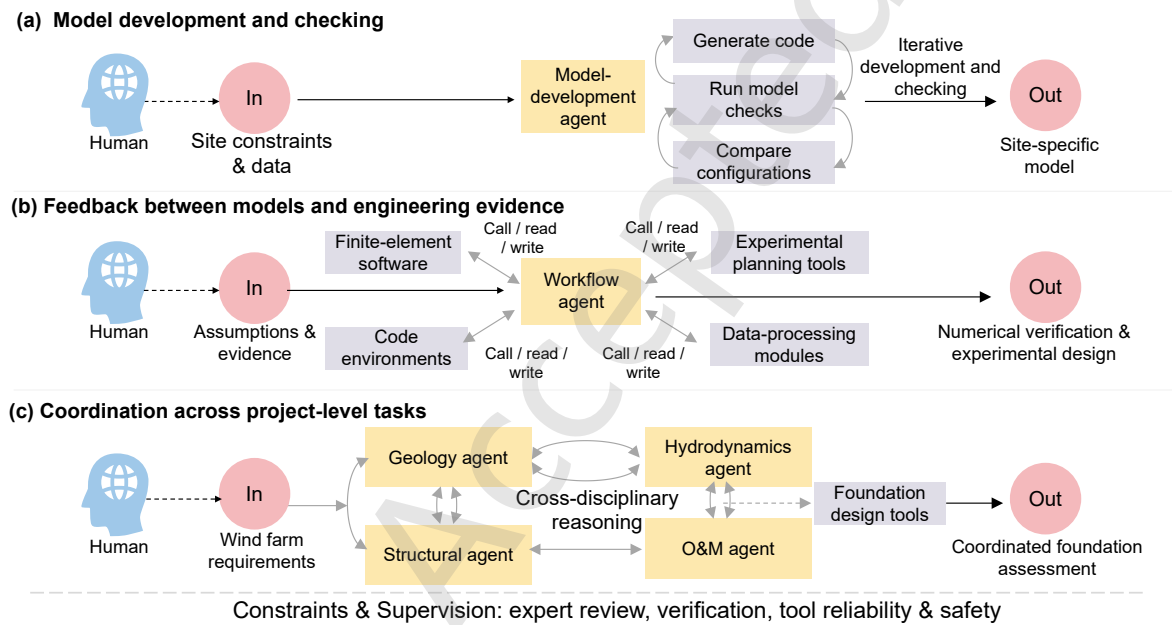


Fig. 11. Three connected levels of agent-assisted workflows in offshore geotechnical engineering: (a) model development and checking, (b) feedback between models and engineering evidence, and (c) coordination across project-level tasks.

At the task level, agents could assist engineers in developing and checking numerical models. For example, Kim et al. used a large language model to generate finite-element code for consolidation, footing settlement, and seepage. They then checked each model against a known solution or experiment. In a broader scientific-machine-learning setting, multi-agent systems have been used to propose, critique, implement, and test models combining data with physical equations [251–253]. Offshore numerical models use the same basic elements, including equations describing soil behavior, site parameters, boundary conditions, numerical solvers, and benchmark

cases. Agents could therefore prepare model inputs, generate code, run parameter studies, and compare results with predefined checks before an engineer accepts the model.

The next level links a model to new evidence, allowing it to be revised as site information becomes available. Pan et al. developed GeoAgent, which searched geotechnical databases and called tools to update uncertain parameters, fill missing data, and map spatial variation. In experimental biology, Ghareeb et al. developed Robin, which searched the literature, proposed experiments, analyzed results, and used the findings to plan the next investigation ^[254,255]. These systems illustrate a common feedback process: evidence is gathered, analyzed with appropriate tools, and used to guide the next step. Offshore geotechnics follows a similar process. Site interpretation informs numerical simulations, while laboratory tests, installation records, and monitoring data may lead engineers to revise the original assumptions. Agents could help organize these comparisons and maintain a traceable record of each update.

Extending this feedback process across an offshore project leads to the third level: coordination among specialized engineering tasks. Youwai et al. developed a system that first identified shallow- or pile-foundation problems and then assigned them to specialized design and checking agents. Vriza et al. organized users, AI agents, and scientific instruments into separate operational levels. Their agents accessed existing equipment through predefined commands and an execution interface ^[256,257].

The workflows above demonstrate how agents can support model development, evidence updating, and task coordination in research and adjacent engineering settings. Transferring them offshore requires adaptation to intermittent connectivity, limited onboard computing, and legacy software. Because current agents often rely on large general-purpose models and online tools, offshore applications need compact, domain-specific agents that can operate locally and connect to existing systems through controlled interfaces. Engineer approval and traceable agent actions must remain

mandatory for design and operational decisions.

6 Conclusions

Overall, AI is moving from isolated prediction toward broader support for offshore wind geotechnical workflows, but the evidence supporting these applications remains uneven across lifecycle stages and engineering tasks. The main conclusions are as follows:

(1) AI in offshore wind geotechnical engineering has evolved from isolated prediction toward project-scale engineering support. In the 266-paper bibliometric corpus, early studies were largely small-sample proof-of-concept efforts; growth accelerated after 2016, and 74.8% of the papers were published during 2021–2025. Over the same period, AI applications broadened from predicting capacity, deformation, and soil classes to surrogate modeling, uncertainty quantification, and monitoring-informed assessment. The use of approximately 1.5 million virtual cone penetration test profiles to construct a tender-stage three-dimensional digital ground model, together with reported applications of surrogate design tools, installation digital twins, and unmanned monitoring systems, shows that this transition has begun to enter project workflows. AI outputs are therefore expanding from one-off predictions to deliverable site models, reusable design tools, and continuously updated representations of engineering states.

(2) Current AI applications remain constrained by data availability and quality, model credibility, transferability, and the requirements of engineering deployment. Field data remain scarce and inconsistently controlled. Even in foundation design, the most extensively studied stage (64.7%), numerical simulations are the primary training source (58.3%). Reported study-level performance is generally high (89.4% of representative R^2 values are at least 0.90), but validation remains predominantly same-source or internal, and field-case evaluation is rare (1.8%). Together with weak physical grounding and interpretability, this validation pattern leaves limited evidence that model performance generalizes across sites, conditions, and time scales. At the deployment level, project applications have entered tendering, installation, and

inspection workflows, but few studies assess whether they improve construction or maintenance outcomes. Standardized pathways for validation, software integration, and certification also remain immature. Current evidence therefore supports AI most clearly for accelerating analysis and assisting state identification; cross-site prediction, closed-loop installation control, and maintenance decision-making still require direct validation against field outcomes.

(3) The current frontiers lie at three connected levels: models, data and evaluation infrastructure, and engineering workflows. At the model level, black-box behavior and insufficient physical constraints remain barriers to engineering review. Physics-informed neural networks and thermodynamics-based artificial neural networks offer routes to strengthen physical consistency, while Kolmogorov–Arnold networks may make input–response relationships more interpretable. At the data level, open site datasets, shared offshore benchmarks, and standardized independent validation and reporting are needed to address proprietary and heterogeneous data and to make results more comparable and transferable. At the workflow level, agent-assisted systems could connect model checking, evidence-based updating, and cross-stage task coordination, although project-scale use still requires direct validation in offshore projects and engineer approval. Together, these directions would make models more interpretable, evidence more comparable, and workflows more reviewable, positioning AI as a bounded complement to established geotechnical analysis and expert judgment.

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Author contribution statement

Jie Shi: Writing-original draft, Conceptualization, Methodology, Formal analysis, Data curation, Visualization, Investigation. **Yimin Lu:** Conceptualization, Supervision, Validation, Writing-review & editing. **Hongjiang Li:** Validation,

Writing-review & editing. **Songyu Liu:** Validation, Writing-review & editing. **Linlong Mu:** Validation, Writing-review & editing. **Hualei Feng:** Data curation, Visualization, Writing-review & editing. **Chuqian Qin:** Data curation, Visualization, Writing-review & editing. **Yunuo Liu:** Data curation, Visualization, Writing-review & editing. **Zhifeng Qin:** Data curation, Visualization, Writing-review & editing. **Zhongkun Ouyang:** Conceptualization, Supervision, Project administration, Funding acquisition, Validation, Writing-review & editing. All authors reviewed and approved the final manuscript.

Data availability

No new experimental or field data were generated in this study. The search strategies and aggregated evidence tables supporting this review are provided in the Supplementary Material. The underlying study-level coding, extracted metric records, screening decisions, and audit files are available from the corresponding authors upon reasonable request.

Declaration of competing interest

All the contributing authors report no conflicts of interest in this work.

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Use of AI statement

None.

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