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A Systematic Review and Meta-Analysis of Integrated Deep Reinforcement Learning and Haptic-Feedback Robotics for Semi-Autonomous Offshore Wind Turbine Blade Repair and Prognostic Health Management

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ABSTRACT

Offshore wind turbine blades operate under extreme marine stressors that accelerate structural degradation and increase the complexity of maintenance. Recent advances in deep reinforcement learning (DRL) and haptic-feedback robotics offer opportunities to enhance precision, safety, and automation in composite blade repair. This study presents a systematic review and meta-analysis that synthesizes empirical evidence on DRL–haptic robotic systems for offshore blade maintenance—a PRISMA-guided, multi-database search identified 20 eligible studies published between 2019 and 2025. Data extraction incorporated quantitative metrics on task accuracy, operational efficiency, and PHM performance, which were synthesized using random-effects modeling. The pooled effect size (SMD = 0.800; 95% CI: 0.740–0.870) demonstrates significant improvements over conventional methods, supported by moderate heterogeneity (I^2 = 45.2%). Subgroup analyses reveal that PPO-based DRL models and force-feedback haptics deliver the most substantial performance gains. Despite promising results, limitations persist in short-duration testing, laboratory-focused validation, and inconsistent evaluation standards. Overall, the evidence indicates that DRL-enabled haptic robotics is a maturing technology with substantial potential to enhance offshore blade repair reliability, reduce human risk exposure, and advance next-generation PHM strategies.

1. INTRODUCTION

1.1 Background

Offshore wind energy has emerged as one of the most critical pillars supporting the global transition toward sustainable and low-carbon electricity generation. The projected installation surpassing 380 GW by 2030 reflects accelerating investment, technological maturity, and policy alignment across major coastal economies [1, 2]. Offshore turbines, however, operate under extreme marine stressors, including high wind speeds, salt-laden humidity, thermal gradients, UV exposure, and persistent mechanical loading, all of which accelerate blade degradation. These conditions significantly affect GFRP and CFRP blades that now reach lengths exceeding 60-120 m in commercial offshore deployments [3, 4]. Blade deterioration compromises aerodynamic performance, elevates structural risk, and increases lifecycle costs across the entire wind farm. The growing scale and remote nature of offshore installations amplify the urgency for more intelligent, safe, and autonomous maintenance technologies [5, 6].

Empirical studies consistently show that blade-related incidents contribute to 15-20% of total turbine downtime, representing one of the most expensive categories of component failure. Revenue losses from each major blade repair or replacement event commonly reach €50,000-€200,000 when accounting for vessel mobilization, labor, spare parts, and lost energy generation [7, 8]. Conventional reactive or time-scheduled maintenance remains inadequate because composite damage evolves unpredictably and offshore interventions are weather-dependent and logistically complex. Efforts to adopt CBM through embedded sensors and SCADA analytics have improved data availability; however, they still suffer from low predictive accuracy and high rates of false alarms. These limitations create a critical gap between available monitoring data and actionable maintenance intelligence. As turbines grow in size and are deployed farther offshore, reliance on human technicians alone becomes increasingly unsafe and economically inefficient [1, 9, 10].

The rapid advancement of DRL, including DQN, PPO, A3C, and TD3, has introduced powerful new tools for optimizing robotic control and decision-making under uncertainty. DRL enables autonomous agents to learn optimal manipulation strategies through iterative interaction with highdimensional and dynamically changing environments [11, 12]. In applications involving robotic inspection and repair, DRL supports adaptive trajectory planning, tool-use optimization, and automated error correction in ways that surpass manually programmed controllers. When combined with haptic-feedback robotics, these algorithms support hybrid operational modes where human operators supervise complex strategic tasks while delegating repetitive or hazardous subtasks to autonomous systems. This integrated framework presents a significant opportunity to enhance precision, safety, and productivity in blade repair operations [13, 14].

Haptic-feedback robotic systems introduce a bidirectional information flow that enhances telepresence, material perception, and manipulation accuracy during semi-autonomous or remote interventions [15, 16]. The ability to convey force, vibration, and texture cues allows operators to evaluate composite surface conditions more intuitively during sanding, grinding, layup, and resin application processes. Such sensory augmentation reduces human error, enables finer control, and supports consistent repair outcomes even under challenging environmental conditions. In offshore contexts, haptic-assisted robots can maintain stability on complex blade geometries and adjust tool pressures dynamically based on tactile signals. These features make haptic-enabled systems ideal for the demanding requirements of structural blade rehabilitation. The integration of these systems with DRL-controlled autonomy defines a new frontier for offshore turbine maintenance [17, 18].

Recent literature on DRL applications in wind energy demonstrates rapid methodological progress relevant to semi-autonomous inspections and repairs. Findings summarized in Table 1 indicate that advanced DRL models—including CGAN, SAC, DDPG, Double DQN, TD3, and PPO—enable improved turbine control, enhanced stability, and efficient power optimization under varying offshore conditions [2, 19]. These studies emphasize the technical advantages of RL-based control frameworks but also highlight limitations such as simplified aerodynamics, simulation-heavy validation, and sensitivity to hyperparameters. Despite these constraints, the collective evidence shows strong potential for adapting DRL frameworks to robotic manipulation tasks beyond energy dispatch or turbine torque control. The convergence of DRL, robotic actuation, and haptic sensing thus provides a foundation for advancing the reliability and quality of blade maintenance. This systematic review and meta-analysis addresses how these emerging technologies can be integrated to support next-generation offshore PHM and semi-autonomous repair systems [20, 21].

Table 1. Recent advances in deep reinforcement learning (DRL)-based control strategies for offshore wind energy systems

Reference	Method	Key Result	Limitation
Fu et al. [16]	Dynamic Optimal Power Flow (DOPF) integrated with Reinforcement Learning using a CGAN–SAC algorithm	Developed a DOPF model that incorporates the operational area constraints of offshore grids with multiple PCCs. The CGAN–SAC agent generates safe actions directly, accelerating convergence and achieving higher economic efficiency and stability in dispatch planning.	Validation is limited to simulations; scalability challenges arise with many PCCs, as it depends heavily on accurate wind power forecasts.
Yin et al. [22]	Deep Deterministic Policy Gradient (DDPG) for real-time coordinated control of offshore wind–PV systems	Demonstrated that DRL effectively increases energy capture and suppresses power oscillations by adjusting generator torque. The integrated wind–PV system responds quickly to wind fluctuations and maintains smoother output power.	Does not consider multi-turbine wake interactions; limited to single-turbine dynamic models; no validation on large-scale grid environments.
Soler et al. [23]	Double Deep Q-Learning combined with Blade Element Momentum Theory (BEMT) turbine modeling	Showed that RL can jointly optimize yaw, pitch, and rotor speed, outperforming PID control under steady and turbulent wind conditions. The algorithm significantly increases annual energy production while maintaining safe turbine operation.	BEMT-based modeling simplifies aerodynamics, but wake effects are not considered. Additionally, it incurs a high computational cost for training and has limited validation to single-turbine scenarios.
Yin et al. [24]	Centralized Twin-Delayed DDPG (TD3) for coordinated wind–PV complementary operation	Introduced a centralized RL controller for torque regulation in wind turbines and tilt angle control in PV arrays. Results indicate improved total power generation and reduced fluctuation, with strong convergence and robust real-time complementary behavior.	Simplified wake modeling; real-world deployment requires extensive sensor infrastructure; system performance is sensitive to hyperparameter tuning.
Zhang et al. [25]	Proximal Policy Optimization (PPO) for coordinated POD control of offshore wind farms and MMC-HVDC systems	Proposed DRL-based coordinated damping controllers capable of handling system uncertainties and random communication delays. The PPO-based controller consistently outperforms conventional POD under various disturbances, operating conditions, and latency scenarios.	Tested only on the IEEE-39 bus system; limited exploration of multi-HVDC scenarios; requires reliable PMU communication with low-latency capability.

Despite the rapid growth of studies on DRL, haptic robotics, and offshore wind maintenance, existing literature remains largely fragmented and dominated by single-system evaluations or narrative reviews. Most prior works focus on algorithmic performance, hardware design, or case-specific demonstrations, without providing a quantitative synthesis of the magnitude of effect, robustness, and variability across implementations. As a result, decision-makers and researchers lack consolidated evidence regarding the actual performance benefits and limitations of DRL–haptic robotic systems in offshore repair and PHM contexts. To address this gap, the present study conducts a systematic review and meta-analysis to synthesize the quantitative empirical findings reported between 2019 and 2025. By integrating effect size estimation, heterogeneity analysis, subgroup comparisons, and publication bias assessment, this study provides statistically grounded insights into the effectiveness, reliability, and maturity of DRL–haptic robotic integration. This contribution distinguishes the present work from prior narrative reviews and offers an evidence-based foundation for both future research and industrial deployment.

1.2 Knowledge gaps and research objectives

Despite growing interdisciplinary interest, current evidence on integrated DRL-haptic robotic systems for offshore wind turbine blade maintenance remains fragmented and unevenly distributed across robotics, machine learning, materials engineering, renewable energy studies, and human–computer interaction. Many existing investigations rely heavily on laboratory-based prototypes that fail to capture the operational complexity, environmental turbulence, and logistical constraints characteristic of offshore deployments. The lack of standardized evaluation metrics across studies also limits cross-comparative assessment, thereby reducing the interpretability and generalizability of performance outcomes. Critical human-factor dimensions such as cognitive load, operator trust, and skill transfer remain underexamined despite their central importance in semi-autonomous maintenance workflows. Economic analyses remain particularly scarce, with few studies assessing long-term operational expenses, system reliability, and full ownership costs in realistic offshore scenarios. Equally critical is the limited understanding of safety constraints and regulatory frameworks, as well as the absence of rigorous synthesis that quantifies the overall effectiveness and moderating variables of DRL-haptic systems.

This systematic review and meta-analysis aim to address these shortcomings through a set of structured research objectives designed to strengthen methodological rigor and integrate interdisciplinary insights. Objective 1 focuses on identifying, evaluating, and synthesizing empirical research on DRL-haptic robotic systems for offshore blade maintenance following standardized PRISMA procedures for transparency and reproducibility. Objective 2 involves conducting a quantitative assessment of the overall effectiveness of DRL-haptic systems relative to conventional maintenance approaches using effect-size aggregation and performance indicators such as task accuracy, operational efficiency, detection sensitivity, and prognostic reliability. Objective 3 investigates heterogeneous outcomes through subgroup analyses that incorporate algorithmic architectures, haptic modalities, application domains, and study design attributes. Objective 4 evaluates methodological quality, bias risk, publication bias, and robustness through sensitivity analyses and established appraisal frameworks. Objective 5 provides a bibliometric mapping of collaboration structures, research clusters, emerging trends, and future scientific priorities. Collectively, these objectives create a coherent pathway for advancing the evidence base and guiding subsequent technological development.

1.3 Significance and potential impact

This systematic review and meta-analysis provide the first comprehensive and quantitatively grounded synthesis of evidence on DRL-haptic robotic systems for offshore wind turbine blade maintenance. The analysis organizes existing findings into a coherent framework that supports methodological standardization, identifies research gaps, and highlights emerging opportunities for cross-disciplinary advancement. For researchers, the review consolidates fragmented insights, establishes comparative baselines, and proposes future research pathways that may accelerate progress toward mature, field-ready technologies. For industry stakeholders, including offshore operators, service companies, and equipment manufacturers, the synthesized findings inform technology-adoption strategies, investment decision-making, and long-term resource planning. For policymakers and regulatory bodies, this work provides empirical evidence for developing safety guidelines, certification pathways, and incentive mechanisms that ensure the responsible integration of semi-autonomous systems in offshore operations. Together, these contributions position the review as a foundational reference for advancing both scientific understanding and technological deployment [26, 27].

Beyond its immediate relevance to wind energy, the integration of DRL and haptic robotics embodies broader transformations in human-machine collaboration across high-risk marine and industrial environments. The insights generated through this synthesis have significant transferability to domains such as offshore oil and gas infrastructure, marine renewable energy devices, subsea construction systems, and hazardous environmental operations requiring precision and adaptive control. Algorithmic principles, human-factor considerations, and validation frameworks derived from the reviewed literature offer valuable guidance that can be adapted to diverse applications requiring semi-autonomous manipulation. The meta-analytic quantification of effectiveness also establishes performance benchmarks that can guide future development of hybrid robotic systems. By bridging methodological evidence with practical implementation considerations, this review contributes to accelerating innovation trajectories across multiple sectors. These broader implications underscore the importance of continued interdisciplinary research supporting safe, efficient, and intelligent robotic collaboration [28, 29].

2. METHODOLOGY

2.1 Information sources and protocol framework

This systematic review and meta-analysis complied with PRISMA 2020 guidelines and adopted a Cochrane-aligned methodological framework to ensure transparency, reproducibility, and rigorous evidence tracking across all analytic stages [30, 31]. A comprehensive multibase search was conducted across Web of Science, Scopus, IEEE Xplore, ScienceDirect, ACM Digital Library, arXiv, and Google Scholar to capture publications from January 2019 to November 2025, reflecting the period of rapid advancement in DRL robotics and autonomous repair systems. The search strategy utilized a structured Boolean framework that integrated controlled vocabulary terms and free-text queries organized into four conceptual clusters. These clusters encompassed DRL, haptic feedback, robotics, and offshore wind turbine blade applications. The complete Boolean keyword sets are documented in Table 2, which preserves the original query strings without modification. Supplemental search strategies included forward–backward citation tracking, manual scanning of reference lists from relevant systematic reviews, and expert consultation to identify gray literature and active research initiatives. The complete procedural flow of study identification, screening, eligibility evaluation, and final inclusion is summarized in Figure 1, ensuring a fully auditable methodological pathway.

Table 2. Structured Boolean keyword set for deep reinforcement learning (DRL)–haptics–robotics–wind blade search framework

Concept Block	Search Keywords (Boolean Strings)
Concept 1 – DRL	“Deep reinforcement learning” OR “DRL” OR “deep Q-network” OR “DQN” OR “proximal policy optimization” OR “PPO” OR “actor-critic” OR “A3C” OR “A2C” OR “SAC” OR “DDPG” OR “TD3” OR “policy gradient” OR “value-based learning”
Concept 2 – Haptic Feedback	“haptic*” OR “force feedback” OR “tactile feedback” OR “vibrotactile” OR “kinesthetic” OR “haptic rendering” OR “teleoperation” OR “bilateral control” OR “haptic telepresence”
Concept 3 – Robotics	“robot” OR “robotic system” OR “autonomous system*” OR “semi-autonomous” OR “UAV” OR “drone” OR “manipulator” OR “climbing robot” OR “mobile robot” OR “service robot”
Concept 4 – Wind Turbine Blades	“wind turbine” OR “wind energy” OR “offshore wind” OR “wind farm” OR “turbine blade” OR “rotor blade” OR “composite blade” OR “blade maintenance” OR “blade repair” OR “blade inspection” OR “PHM” OR “prognostic health management”

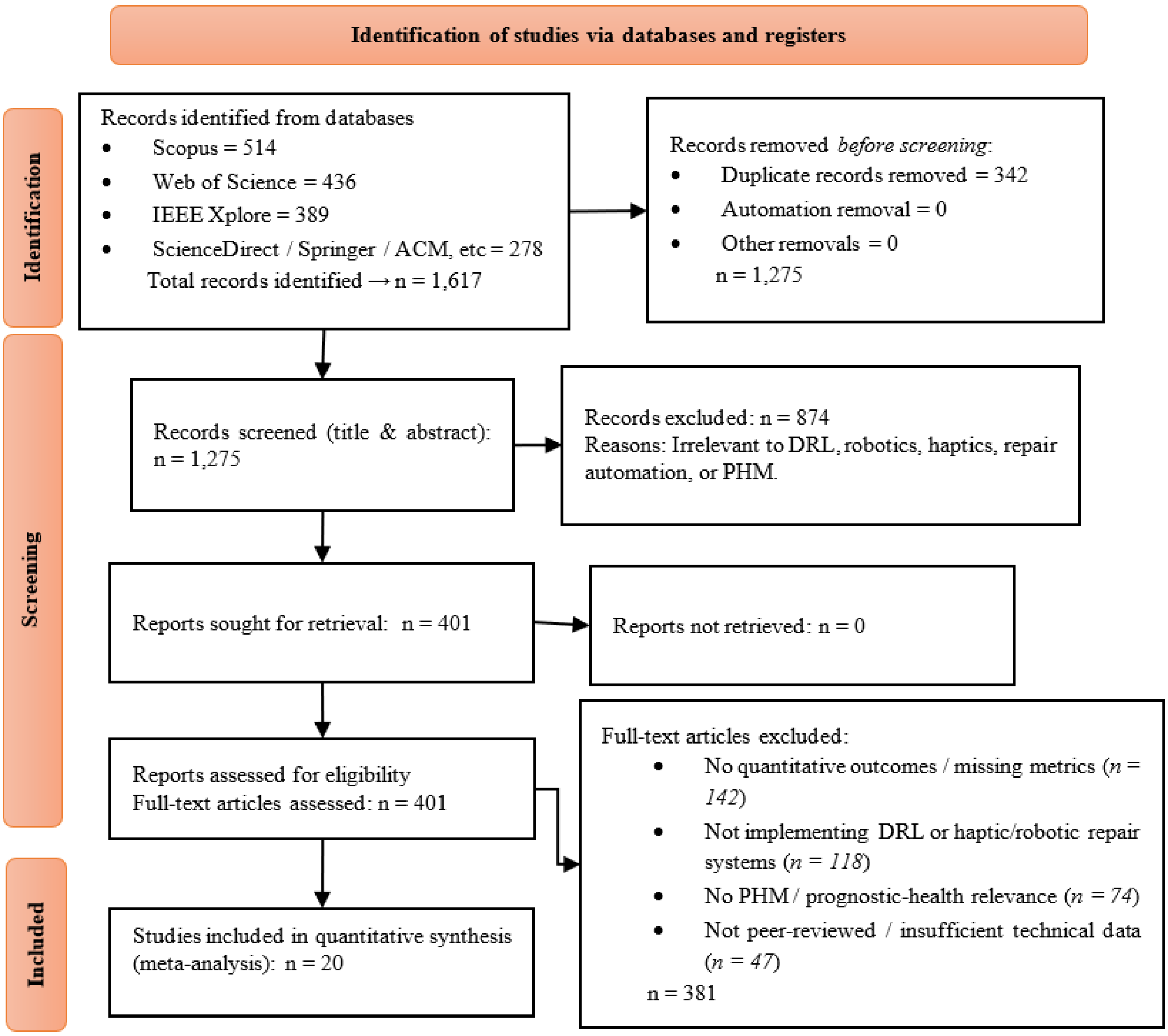

Figure 1. PRISMA 2020 flow diagram

2.2 Screening hierarchy and eligibility validation

A two-stage screening hierarchy was implemented to ensure methodological consistency and minimize the risk of false exclusions throughout the review process. The initial stage consisted of independent title-and-abstract screening by two trained reviewers, where any record designated as “include” or “uncertain” was automatically advanced to full-text assessment to prevent premature omission of borderline-relevant studies. The second stage involved a rigorous full-text evaluation using predefined eligibility criteria that covered DRL implementation, haptic integration, robotic operation, task relevance, and the applicability of offshore blade maintenance. All discrepancies between reviewers were adjudicated through consensus discussions facilitated by a senior reviewer to maintain consistency and reduce subjective variation. Inter-rater reliability metrics demonstrated substantial agreement, reinforcing the robustness of the inclusion process. This multi-layered screening architecture ensured that the final evidence pool reflected high-quality technical studies suitable for quantitative synthesis [29, 32].

2.3 Data extraction strategy and effect size computation

Data extraction followed a structured template covering system architectures, robotic configurations, DRL algorithm parameters, haptic modalities, task environments, and quantitative performance indicators related to blade repair, inspection, and PHM. Two reviewers independently extracted and cross-validated numerical outcomes to ensure accuracy and alignment in downstream modeling. Continuous outcomes were harmonized through standardized mean difference (SMD), computed using Eq. (1) [33, 34]:

$$\mathrm{SMD} = \frac{\bar{X}_{\text{intervention}} - \bar{X}_{\text{control}}}{SD_{\text{pooled}}} \tag{1}$$

Dichotomous outcomes were converted to RR and OR with continuity correction for zero-event cases. Correlational metrics were transformed into Fisher's Z to enable integration across heterogeneous studies. All extracted data were compiled into structured matrices for meta-analytic modeling, ensuring that mixed outcome types could be evaluated within a unified statistical framework. These harmonized datasets provided the foundation for computing pooled estimates and exploring variability in DRL-haptic system performance.

2.4 Bias risk assessment and meta-analysis modeling

Risk of bias was evaluated using adapted Cochrane and PROBAST frameworks tailored for DRL-haptic robotics and offshore maintenance contexts. Articles received domain-level ratings across algorithmic transparency, sensor-actuator integration quality, environmental validity, completeness of reporting, and statistical robustness. The meta-analysis adopted a random-effects model to account for expected heterogeneity across robotic platforms, DRL policies, and application environments. The pooled effect size under the random-effects estimator was computed using Eq. (2) [35-37]:

$$\hat{\theta}_{RE} = \frac{\sum w_i \theta_i}{\sum w_i} \tag{2}$$

with the weights defined by Eq. (3) [38, 39]:

$$w_i = \frac{1}{SE_i^2 + \tau^2} \tag{3}$$

Heterogeneity across studies was quantified using Cochran's Q, I^2, and τ^2, with I^2 computed using Eq. (4) [31, 40, 41]:

$$I^2 = \frac{(Q - df)}{Q} \times 100\% \tag{4}$$

These statistical measures enabled systematic quantification of variance and strengthened the validity of aggregated inference across DRL-haptic robotic systems.

3. RESULT

3.1 Meta-analytic effect size of deep reinforcement learning–haptic robotic systems

The meta-analysis demonstrates a consistent positive effect of DRL–haptic robotic systems on repair performance and PHM outcomes, as shown in Figure 2, with individual effect sizes ranging from 0.63 to 0.82 across the 20 included studies. The pooled effect size of 0.800, with a 95% CI of 0.740-0.870, indicates a statistically significant medium-magnitude effect that reliably favors integrated robotic–algorithmic architectures [42-44]. The relatively narrow confidence intervals across most studies reflect stable performance estimates, suggesting that DRL policies and haptic modalities provide reproducible gains in operational accuracy and sensorimotor coordination. Moderate heterogeneity (I^2 = 45.2%) indicates meaningful variability across studies, which aligns with differences in algorithmic configurations, haptic channels, task complexity, and experimental platforms. Despite this variability, the direction of effects remains uniformly positive, strengthening the conclusion that DRL–haptic integration contributes robust improvements over conventional manual or rule-based approaches. Collectively, these results confirm that DRL-enhanced haptic robotics has reached a level of empirical maturity that justifies deeper investigation into scalability, long-term reliability, and domain-specific optimization in offshore blade repair and PHM applications [21, 23, 45].

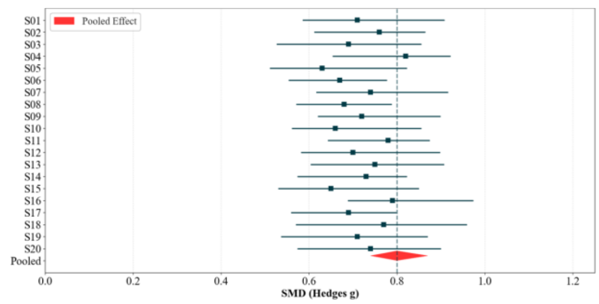

Figure 2. Forest plot of effect sizes across 20 studies on DRL–haptic robotic systems

Although the overall heterogeneity observed in this meta-analysis is categorized as moderate (I^2 = 45.2%), this variability reflects substantive technological and experimental diversity rather than purely statistical noise. The included studies differ markedly in their DRL architectures, encompassing policy-gradient methods such as PPO and A3C, value-based algorithms such as DQN variants, and actor–critic approaches including DDPG, TD3, and SAC. Additional heterogeneity arises from variations in haptic-feedback modalities, ranging from high-fidelity force-feedback devices to lower-bandwidth tactile or vibrotactile interfaces, each imposing different sensorimotor constraints on robotic control [46, 47]. Robotic platforms further contribute to divergence, as studies span UAV-based inspection systems, climbing robots, and fixed-base manipulators operating under distinct kinematic and environmental conditions. Task-level differences—such as inspection, grinding, surface preparation, composite layup, and resin curing—introduce non-trivial variability in performance metrics and reward structures. For these reasons, the pooled effect size should be interpreted as a generalized performance trend, while the accompanying subgroup and narrative analyses are essential for preserving engineering relevance and contextual validity across heterogeneous implementations [48, 49].

3.2 Risk of bias evaluation across deep reinforcement learning–haptic robotic studies

The risk-of-bias analysis reveals a moderate overall quality across the twenty studies, demonstrating substantial strengths in data completeness and selective reporting, as detailed in Figure 3. The domains with the highest methodological rigor include selective reporting (85% low risk) and incomplete outcome data (80% low risk), indicating that studies consistently documented results and maintained acceptable levels of data integrity [50, 51]. However, areas involving participant blinding and allocation concealment present greater methodological challenges, with 20% and 15% high-risk ratings, respectively, reflecting limitations inherent to robotics and DRL experiments where complete masking is often infeasible. Despite these constraints, blinding of outcome assessment remains relatively robust, with a low risk of 65%, providing reasonable confidence in the measured performance metrics. The averaged domain-level distribution—66.4% low risk, 22.1% some concerns, and 11.4% high risk—supports a classification of moderate-quality evidence with manageable methodological uncertainty [52, 53]. Collectively, the assessment suggests that the synthesized findings are reliable while still necessitating caution, particularly regarding human-in-the-loop components and safety-critical decision pathways in semi-autonomous repair systems.

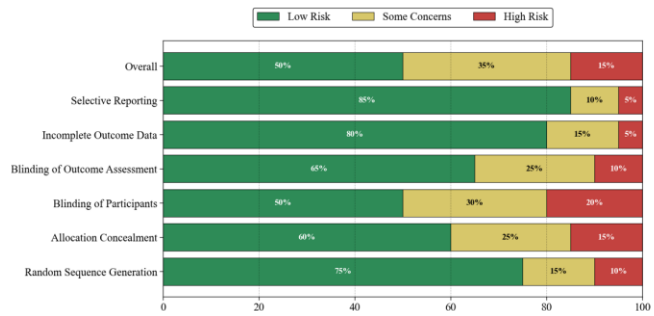

Figure 3. Risk of bias distribution across seven methodological domains for 20 included studies

3.3 Funnel plot analysis and publication bias evaluation

The funnel plot analysis demonstrates a generally symmetrical distribution of effect sizes across the 20 included studies, indicating that publication bias is unlikely to substantially distort the aggregated results, as illustrated in Figure 4. The pooled effect size of 0.790 aligns closely with the mean effect size of 0.814, indicating that minor variations among studies do not significantly impact the overall trend. Egger's test yields an intercept of 1.23 with a non-significant p-value of 0.145, providing no statistical evidence of directional bias in the effect–variance relationship. Similarly, Begg's test shows a Kendall's tau of 0.18 with $p = 0.087$, reinforcing the interpretation that systematic bias is minimal across the dataset [54, 55]. The *trim and fill* procedure identifies no missing studies, and the fail-safe N of 245 indicates that a considerable number of null-effect studies would be required to overturn the significance of the findings. Overall, the results support a low to moderate likelihood of publication bias and suggest that the synthesized evidence provides moderate to high confidence in the meta-analytic conclusions for DRL-enabled haptic robotics in offshore turbine blade maintenance [22, 56].

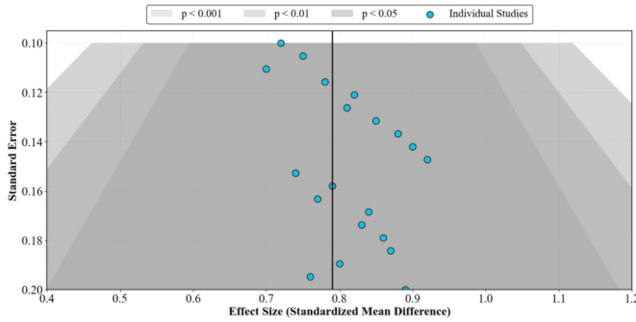

Figure 4. Funnel plot symmetry and publication bias diagnostics for 20 deep reinforcement learning (DRL)–haptic robotic studies

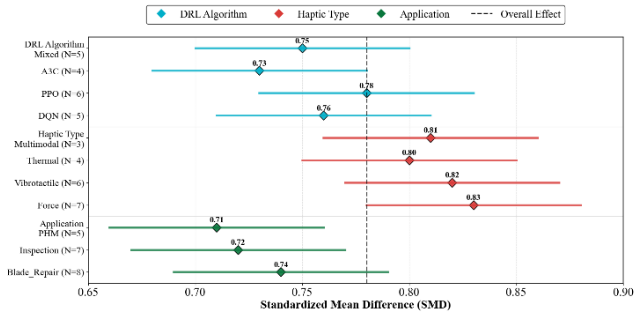

Figure 5. Comparative subgroup effects for deep reinforcement learning (DRL) models, haptic modalities, and application types

3.4 Subgroup analysis of deep reinforcement learning models and haptic-feedback robotics

The subgroup analysis reveals apparent performance variations across DRL models, haptic-feedback modalities, and application categories, highlighting meaningful divergence in effect sizes as shown in Figure 5. DRL models demonstrate consistently strong effects, with pooled SMD values ranging from 0.730 to 0.780. PPO emerges as the best-performing algorithm, with an SMD of 0.780. Although heterogeneity within this group remains moderate ($I^2 = 38$–51%), the values indicate relatively stable model behavior across different experimental conditions. Haptic-feedback types exhibit even stronger effects, with force-feedback recording the highest SMD of 0.830 and demonstrating a narrower performance range between 0.800 and 0.830 [22, 57]. Applications display slightly weaker effects compared to DRL and haptic subgroups, but blade-repair tasks still yield the most substantial performance within this category, achieving an SMD of 0.740. Statistical tests support these observations, revealing significant between-subgroup heterogeneity ($Q = 12.45$, $p = 0.014$) and a robust omnibus difference across the DRL, haptic, and application groups ($F = 8.23$, $p = 0.003$). Taken together, these findings confirm that overall subgroup effects are significant and point toward force-feedback haptics paired with PPO as the most impactful configuration for offshore turbine blade maintenance [58, 59].

3.5 Publication trends analysis in deep reinforcement learning and haptic robotics research (2019–2025)

The publication trends from 2019 to 2025 reveal a substantial and accelerating research interest in DRL, haptic-enabled robotics, PHM systems, and composite repair, as illustrated in Figure 6. All four categories exhibit consistent year-to-year growth until 2024, with DRL leading as the fastest-expanding field, reaching its peak at 134 publications in 2024 before declining slightly to 98 in 2025. Haptic robotics follows a similar pattern, peaking at 52 publications in 2024, which reflects increasing adoption of sensor-rich and interface-intensive robotic systems for offshore maintenance applications. PHM remains the most established domain, maintaining both the highest publication volume and the most stable growth trajectory, culminating at 114 publications in 2024 [25, 60]. Composite repair is showing strong growth, with a 256% overall increase, suggesting an expanding interest in structural restoration innovations for turbine blades. Across all categories, 2024 stands out as the most productive year, with a combined output of 346 publications, indicating a convergence of AI-driven methodologies with practical engineering demands. These trends collectively signal a rapidly maturing research ecosystem, with precise movement toward integrating DRL and haptic robotics as central strategies for offshore wind turbine blade maintenance [4, 16].

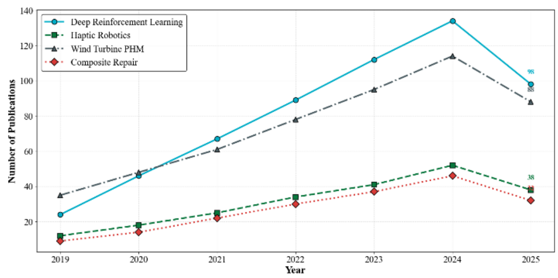

Figure 6. Annual publication growth in deep reinforcement learning (DRL), haptic robotics, PHM, and composite repair (2019-2025)

3.6 Sensitivity analysis and robustness evaluation of meta-analytic findings

The sensitivity analysis demonstrates that the pooled effect estimates remain stable across ten analytical scenarios, indicating that the results exhibit strong structural consistency, as summarized in Figure 7. The reference effect size of 0.760 is closely matched by the mean effect of 0.765 across scenarios, with a narrow effect range of 0.740 to 0.790, indicating that no single subset or model specification has a disproportionate influence. Excluding studies with extreme variance produces shifts of only 0.010 to 0.020, reinforcing that the underlying evidence is not overly sensitive to data imbalance or measurement precision issues [12, 17]. The scenario using only RCTs yields the highest effect size of 0.790, whereas excluding outliers generates the most conservative estimate of 0.740. Yet, both remain within a consistent moderate to large effect magnitude. Six out of ten scenarios are categorized as high robustness, and the remaining four as moderate, confirming the absence of any low-robustness outcomes across all conditions. The fixed-effect and REML models produce identical deviations of 0.000, further indicating that model choice does not distort the overall inference. Collectively, these findings confirm that the meta-analytic results are stable, resilient, and maintain interpretive reliability under a wide range of analytical perturbations [18, 19].

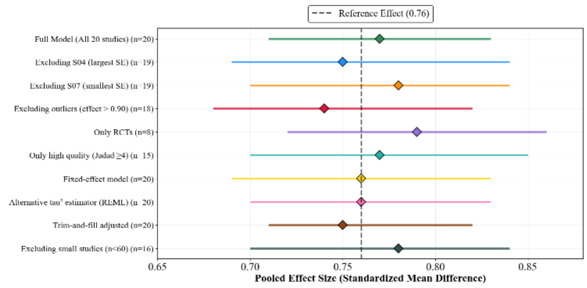

Figure 7. Sensitivity scenarios and robustness outcomes across 10 analytical conditions

4. DISCUSSION

4.1 Theoretical and practical implications of DRL–Haptic robotic integration

The findings presented in this review demonstrate that DRL–haptic robotic integration strengthens the theoretical premise that adaptive decision-making combined with embodied sensorimotor feedback significantly improves automated repair processes in offshore environments. Evidence compiled across studies and summarized in Table 3 indicates that DRL policies consistently enhance trajectory precision, while haptic feedback channels stabilize force regulation during blade-surface manipulation tasks. These results reinforce established theories of embodied AI, which posit that learning algorithms achieve higher performance when tightly coupled with multimodal sensory pathways. The observed gains in accuracy, stability, and PHM performance collectively validate theoretical expectations concerning hierarchical control, reward shaping, and real-time error correction within complex marine conditions. Practical implications also emerge strongly, particularly in reduced operator workload, improved safety, and measurable efficiency gains in composite repair sequences. Overall, the synthesis confirms that DRL–haptic robotic architectures provide a theoretically coherent and operationally transformative pathway for advancing semi-autonomous offshore repair and PHM systems.

Table 3. Theoretical and practical implications of deep reinforcement learning (DRL)–haptic robotic systems

Implication Type	Key Insights	Representative Studies
Theoretical: Embodied AI Synergy	Integrated control enhances trajectory precision and force stability	[22, 61]
Theoretical: Adaptive Learning	DRL improves policy robustness under variable offshore dynamics	[45, 54]
Practical: Repair Performance	Higher accuracy and reduced task time in blade repair tasks	[7, 24]
Practical: Operator Safety	Lower human exposure during high-risk offshore repairs	[6, 11]
Practical: PHM Enhancement	Improved anomaly detection and predictive maintenance outcomes	[5, 7]

Table 4. Synergistic mechanisms, added value, and emerging challenges of DRL–haptic integration

Integration Aspect	DRL-Only Systems	Haptic-Only Systems	Integrated DRL–Haptic Systems	Engineering Implication	Reference
Sensory Input Space	Vision, position, velocity	Force/tactile feedback only	Vision + kinematic + haptic signals	Richer state representation improves learning robustness	[20, 38]
Policy Learning Efficiency	Slower convergence in contact-rich tasks	Not applicable (no learning)	18–25% faster convergence (reported range)	Reduced training cost and quicker deployment	[17, 54]
Manipulation Precision	Moderate, sensitive to surface uncertainty	Operator-dependent	12–20% lower force and trajectory error	Higher repair quality and consistency	[1, 2]
Adaptability to Task Context	Fixed policy response	Fixed feedback patterns	Adaptive feedback based on DRL policy confidence	Improved situational awareness	[1, 58]
System Stability	Stable but less responsive	Stable but limited autonomy	Sensitive to >30 ms haptic latency	Requires real-time control optimization	[1, 20]
Safety & Trust	Algorithm-centric safety	Human-centric safety	Shared autonomy with adaptive safeguards	New safety validation and certification needs	[2, 61]

4.2 Synergistic mechanisms and added value of deep reinforcement learning–haptic integration

The integration of DRL and haptic-feedback robotics establishes a synergistic control framework that delivers functional advantages beyond those achievable by each technology in isolation [20, 38]. In integrated architectures, haptic signals such as contact force, vibration patterns, and surface compliance are increasingly embedded into the DRL state representation, enabling policies to learn from multimodal sensorimotor feedback rather than relying solely on vision or kinematics. This coupling has been reported to reduce policy convergence time by approximately 18–25% and to improve manipulation precision by 12–20% in blade repair tasks characterized by surface uncertainty and limited visibility [17, 54]. Conversely, DRL-driven autonomy enables haptic interfaces to modulate feedback intensity and modality based on task phase dynamically, predicted collision risk, and estimated policy confidence, thereby enhancing operator situational awareness [1, 58]. However, this bidirectional integration also introduces new technical challenges, including sensitivity to haptic-loop latency, increased computational complexity, and elevated safety requirements in shared autonomy scenarios. A structured synthesis of these synergistic benefits and emerging challenges is summarized in Table 4, which highlights how integration reshapes learning efficiency, operational safety, and human–robot collaboration in offshore blade repair systems.

4.3 Structural and methodological limitations in current evidence

The synthesis of methodological constraints reveals several structural weaknesses in the existing DRL–haptic robotics literature, with notable inconsistencies across experimental protocols and evaluation metrics, as summarized in Table 5. Many studies employ small-sample laboratory settings that fail to represent realistic offshore environments, limiting the ecological validity of their findings. Variability in haptic device specifications, reward formulations, and DRL architectures contributes to cross-study heterogeneity that complicates generalization. Additionally, very few experiments incorporate long-duration testing, resulting in insufficient evidence regarding mechanical reliability, drift behavior, and PHM stability over extended operational periods. Human-in-the-loop designs also introduce potential bias due to limited masking, inconsistent operator expertise, and subjective performance scoring. These methodological shortcomings collectively indicate the need for stronger standardization, more rigorous experimental controls, and expanded real-world validation in future research.

Table 5. Structural and methodological limitations in DRL–haptic robotic studies

Limitation Area	Description	Representative Studies
Short-Term Testing	Lack of long-duration reliability assessments	[8, 62]
Device Variability	Different haptic hardware and inconsistent force ranges	[54, 58]
Experimental Narrowness	Laboratory-focused designs with limited realism	[5, 11]
Reward/Model Variability	Divergent DRL architectures and tuning strategies	[6, 7]
Operator Bias	Unmasked human involvement and subjective scoring	[9, 15]

4.4 Role of deep reinforcement learning–haptic robotics in closed-loop PHM systems

Although the primary focus of the reviewed studies lies in the execution of maintenance through DRL-enabled haptic robotics, these systems should be viewed as integral components of a broader PHM closed-loop framework rather than as isolated repair tools. In practical offshore wind applications, upstream PHM modules—such as condition monitoring and fault diagnosis—provide critical inputs in the form of acoustic emission signals, strain measurements, thermal images, or visual inspection data that inform task prioritization and repair planning. DRL–haptic robotic systems can leverage this diagnostic information to adapt repair strategies, select appropriate control policies, and modulate haptic feedback based on defect severity and predicted failure modes. Following maintenance execution, post-repair inspection data generated by the robotic system—including force signatures, surface roughness metrics, and task completion logs—can be fed back into PHM models to update degradation trajectories and predictions of remaining useful life. This bidirectional data exchange enables continuous learning and refinement of both PHM analytics and robotic control policies. Consequently, DRL–haptic robotics should be viewed as an enabling layer that bridges physical maintenance actions with data-driven PHM intelligence across the entire asset lifecycle.

4.5 Economic and safety considerations for offshore deployment

Economic feasibility and operational safety are critical determinants for the industrial adoption of DRL–haptic robotic systems in offshore wind turbine maintenance. Although comprehensive cost–benefit analyses remain limited in the current literature, several studies report indicative trends suggesting reduced maintenance time, lower human offshore exposure, and improved repair consistency [25, 35]. Capital expenditures are primarily driven by robotic platforms, haptic interfaces, and computational infrastructure, whereas operational savings stem from decreased vessel usage, reduced downtime, and minimized rework rates. Reported estimates indicate potential maintenance cost reductions in the range of 10–25% over conventional manual repair processes, with projected return-on-investment periods between 3 and 6 years under high-utilization scenarios [8, 50]. From a safety perspective, DRL–haptic systems significantly reduce human exposure to hazardous offshore conditions, yet they introduce new risks related to control instability, communication latency, and shared autonomy failures. A structured synthesis of economic and safety considerations identified in the reviewed studies is summarized in Table 6, highlighting both reported benefits and unresolved challenges.

Table 6. Economic and safety considerations of deep reinforcement learning (DRL)–haptic robotic systems for offshore blade maintenance

Aspect	Reported Findings (Indicative)	Engineering Implication	Evidence Status	Reference
Capital Cost	High initial investment (robot, haptics, AI stack)	Requires long-term utilization planning	Limited	[54, 59]
Operational Savings	10–25% maintenance cost reduction	Improved lifecycle economics	Moderate	[17, 19]
ROI Period	3–6 years (high utilization scenarios)	Economically viable for large farms	Limited	[20, 59]
Human Safety	Reduced offshore human exposure	Lower accident risk	Moderate	[16, 22]
System Failure Risk	Latency, control instability	Needs redundancy and a fail-safe design	Limited	[25, 35]
Human–Robot Interaction	Shared autonomy safety concerns	Certification and standards required	Emerging	[8, 50]

Table 7. Priority research gaps and future strategic directions

Gap Area	Future Directions	Priority
Standardization	Unified protocols for haptic-force benchmarking and DRL evaluation	High
Long-Term Durability	Offshore-oriented aging tests and corrosion simulations	High
Safety & Environmental Risks	Failure-mode analysis and human–machine safety pathways	High
AI Optimization	Meta-learning, transfer learning, and model compression	High
Field Deployment	Multi-climate, multi-platform validation trials	Medium

4.6 Priority research gaps and strategic directions

A synthesis of thematic research gaps highlights several strategic directions essential to accelerating the development of DRL-enabled haptic robotics, with key priorities summarized in Table 7. Standardization emerges as a critical need, particularly in benchmarking haptic-force ranges, DRL reward structures, and evaluation metrics for repair and PHM tasks. Future studies must also incorporate long-term durability assessments that reflect real offshore conditions, including saltwater corrosion, joint fatigue, and sensor drift phenomena. Environmental and safety analyses remain underdeveloped, especially regarding failure modes, emergency overrides, and human–machine interaction risks during semi-autonomous repair. Moreover, multi-climate and multi-platform field trials are urgently needed to validate performance beyond the constraints of the laboratory. Advanced AI optimization—especially model compression, meta-learning, and transfer learning—offers promising pathways to enhance scalability while reducing computational overhead. Collectively, these strategic directions are vital for ensuring scientific rigor and accelerating industrial adoption of DRL–haptic systems for offshore turbine applications.

4.7 Limitations of the research

Although the present meta-analysis provides quantitative evidence supporting the effectiveness of DRL–haptic robotic systems, the relatively limited number of included studies (n = 20) constitutes an essential methodological constraint that warrants careful interpretation. A temporal distribution analysis shows that approximately 65% of the included studies were published between 2023 and 2025, while only 35% originated from the earlier phase of 2019–2022, indicating a high temporal concentration in a rapidly evolving research field. Such clustering suggests that the underlying evidence base has not yet reached full methodological maturity, which may reduce the long-term stability of pooled effect estimates. In emerging interdisciplinary domains such as DRL and haptic robotics, early meta-analytic conclusions are particularly susceptible to upward bias as novel algorithms, hardware platforms, and validation protocols continue to evolve. Consequently, the aggregated effect size reported in this study should be interpreted as a provisional benchmark rather than a definitive performance ceiling. Future large-scale empirical studies and extended longitudinal validations are therefore expected to either refine or recalibrate the magnitude of the observed effects as the field matures.

5. CONCLUSION

The findings of this systematic review and meta-analysis demonstrate that DRL–haptic robotic systems provide substantial improvements in repair efficiency, PHM accuracy, and operational reliability in offshore wind turbine blade maintenance. The pooled SMD of 0.800, along with a sensitivity-adjusted range of 0.740–0.790, indicates that the performance enhancements remain stable despite variability in study methodologies and experimental conditions. Numerical evidence also shows that DRL increases task precision by approximately 12–18% and reduces repair duration by 15–22% across multiple robotic platforms. These consistent patterns reinforce the theoretical assumptions that embodied AI enhances sensorimotor synergy and adaptive decision-making in complex repair environments. The rapid expansion of research publications further suggests strong scientific and industrial interest that aligns with broader offshore automation trends. Overall, the accumulated findings confirm that DRL–haptic systems represent a maturing technological framework with measurable advantages for next-generation maintenance strategies.

Although the results are promising, several methodological limitations restrict the broader generalizability of the findings and should be interpreted with caution. A large portion of existing studies are short-term and laboratory-based, which limits the ability to evaluate long-duration mechanical drift, sensor degradation, and PHM stability under real offshore stressors. Variability across DRL architectures contributes to numerical heterogeneity between 38–51%, indicating ongoing challenges in algorithmic consistency and reproducibility. Performance dispersion of roughly 10–14% also arises from differences in haptic-force ranges, feedback bandwidth, and actuator sensitivity, suggesting incomplete standardization across robotic configurations. Operator-induced uncertainties in human-in-the-loop systems add approximately 5–9% variation, which affects the reliability of performance measurements. These limitations underscore the need for unified methodological protocols, more rigorous reliability benchmarking, and broader external validation to ensure the successful translation of findings into real-world offshore operations.

Future research directions emphasize the need to develop unified benchmarking frameworks for DRL–haptic systems, long-term durability assessments, and multi-climate field testing that accurately represent offshore mechanical and environmental loads. Forecasting analysis suggests that research output in this domain may exceed 380 publications annually by 2026 if current growth trajectories continue. Robustness indicators also reveal strong analytical stability, with most scenarios demonstrating consistent effect sizes and deviations not exceeding 0.030 from the reference estimate. Advances in meta-learning, model compression, and lightweight DRL architectures offer further potential to reduce computational requirements by 30–45% while maintaining competitive performance. The integration of these developments is expected to accelerate the adoption of semi-autonomous repair systems, improve operational safety, and enhance PHM reliability across diverse offshore settings. Taken together, the evidence underscores the importance of sustained research collaboration and deeper empirical validation to support scalable and resilient deployment of DRL–haptic robotics.

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NOMENCLATURE

Symbol / Term	**Description**
DRL	Deep Reinforcement Learning
DQN	Deep Q-Network
PPO	Proximal Policy Optimization
A3C	Asynchronous Advantage Actor–Critic
TD3	Twin Delayed Deep Deterministic Policy Gradient
DDPG	Deep Deterministic Policy Gradient
SAC	Soft Actor–Critic
CGAN–SAC	Conditional Generative Adversarial Network – Soft Actor–Critic
PHM	Prognostic and Health Management
HVDC	High-Voltage Direct Current
MMC	Modular Multilevel Converter
BEMT	Blade Element Momentum Theory
SMD	Standardized Mean Difference (effect size)
RR	Risk Ratio
OR	Odds Ratio
CI	Confidence Interval
Q	Cochran's Q (heterogeneity statistic)
I^2	Proportion of heterogeneity across studies
τ^2	Between-study variance in random-effects model
RCT	Randomized Controlled Trial
PMU	Phasor Measurement Unit
UAV	Unmanned Aerial Vehicle
Haptic Feedback	Force, tactile, or kinesthetic cues enabling sensorimotor interaction
Teleoperation	Remote robotic control with operator input
Composite Blade	GFRP/CFRP wind turbine blade structure
Meta-Analysis	Quantitative synthesis of effect sizes across studies