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Research Article

ALGORITHMIC INTELLIGENCE IN ENGINEERING DESIGN: INTEGRATING MACHINE LEARNING WITH PHYSICAL MODELING

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Abstract
Increasing complexity in engineering systems demands design methodologies that balance computational efficiency, predictive accuracy, and physical reliability. Traditional physics-based simulations ensure mechanistic consistency but are computationally expensive, while purely data-driven machine learning models offer speed yet often lack interpretability and physical compliance. Integrating algorithmic intelligence with physical modeling has therefore emerged as a promising paradigm in advanced engineering design. This study aims to develop and evaluate a hybrid framework that integrates machine learning algorithms with governing physical equations to enhance design performance, robustness, and computational efficiency. A mixed-methods computational design was employed using 15,000 high-fidelity simulation datasets across structural, aerodynamic, and thermal engineering cases. Three modeling configurations physics-based models, data-driven models, and hybrid physics-informed machine learning modelswere comparatively analyzed using performance metrics including mean squared error, R^2, runtime efficiency, robustness testing, and constraint violation indices. Statistical analyses were conducted to determine significance of performance differences. Hybrid models achieved superior balance, reaching $R^2 = 0.97$ with significantly reduced runtime compared to physics-based simulations ($p < 0.001$), while maintaining substantially lower physical constraint violations than purely data-driven models. Sensitivity and uncertainty analyses confirmed enhanced robustness under parameter perturbation. Algorithmic intelligence integrated with physical modeling represents an epistemologically coherent and practically effective approach, advancing engineering design toward trustworthy, efficient, and physically consistent computational frameworks.

Keywords: Engineering Design, Machine Learning, Physics-Informed Modeling

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INTRODUCTION

Engineering design has entered an era characterized by increasing system complexity, multi-physics interactions, and stringent performance requirements across industries such as aerospace, automotive, energy, and biomedical engineering. Traditional design methodologies have relied heavily on physics-based modeling, numerical simulation, and optimization techniques grounded in first principles (EL Hannaoui & Boutarfa, 2025; Thawon et al., 2025). Finite element analysis, computational fluid dynamics, and multi-body dynamics have enabled engineers to predict system behavior with considerable accuracy. Rapid growth of data availability and computational power, however, has introduced algorithmic intelligence and machine learning as transformative tools capable of extracting patterns beyond conventional analytical formulations (Sultan et al., 2025).

Machine learning techniques have demonstrated remarkable success in pattern recognition, surrogate modeling, predictive maintenance, and real-time control. Data-driven models can approximate complex nonlinear relationships that are computationally expensive to simulate using high-fidelity physics-based solvers (Tezcan & Efeoğlu, 2025; Zvarivadza et al., 2025). Emergence of hybrid modeling approaches combining physical laws with data-driven learning has generated interest in creating more adaptive, efficient, and robust engineering design frameworks. Integration of these paradigms promises accelerated design cycles, reduced computational cost, and enhanced decision-making under uncertainty (Huang et al., 2025).

Engineering design increasingly demands integration rather than substitution of methodologies. Purely physics-based models may suffer from simplifications and parametric uncertainty, whereas purely data-driven systems may lack interpretability and physical consistency (Kasaie & Rajendran, 2023; Mehraban et al., 2025). Convergence of machine learning and physical modeling represents a paradigm shift toward algorithmic intelligence embedded within scientific principles. This transformation raises foundational questions about model fidelity, generalizability, interpretability, and epistemological coherence in design processes (El-Mesery et al., 2025).

Despite rapid advances in machine learning applications within engineering, significant challenges persist in integrating algorithmic intelligence with physics-based modeling. Data-driven models often operate as black boxes, limiting interpretability and trustworthiness in safety-critical design contexts (Didi et al., 2025). Engineering decisions require explainable reasoning grounded in physical laws, yet many machine learning architectures prioritize predictive accuracy over mechanistic understanding. Tension between performance optimization and physical interpretability creates uncertainty regarding the reliability of hybrid systems (Ge et al., 2025).

Limitations also arise in the availability and quality of training data. Engineering design problems frequently involve rare failure events, high-dimensional parameter spaces, and multi-scale phenomena that are difficult to capture comprehensively in datasets (Mohammadnezhad et al., 2025). Data scarcity can lead to overfitting, poor generalization, and unstable predictions when machine learning models are extrapolated beyond observed conditions. Purely physics-based simulations, although computationally expensive, provide consistent theoretical grounding that data-driven models may lack (Basem et al., 2025; Xu et al., 2025).

Methodological fragmentation further complicates integration efforts. Existing research often treats machine learning as an auxiliary surrogate model or optimization enhancer rather than as an epistemologically integrated component of physical modeling (Aljehani, 2025; Yang et al., 2025). Lack of standardized frameworks for coupling learning algorithms with governing equations limits scalability and reproducibility. Engineering design therefore faces a critical problem: how to construct coherent hybrid systems that maintain physical integrity while leveraging algorithmic intelligence for efficiency and adaptability (T. Yao et al., 2025).

This study aims to develop a conceptual and methodological framework for integrating machine learning with physics-based modeling in engineering design. Objective involves identifying structural compatibilities between algorithmic learning mechanisms and governing physical laws. Analytical focus centers on determining how machine learning models can enhance, rather than replace, physical simulations (Liang et al., 2025).

Research further seeks to evaluate performance, robustness, and interpretability of hybrid models in comparison to standalone approaches. Quantitative assessment of predictive accuracy, computational efficiency, and sensitivity to uncertainty forms a core component of the investigation. Comparative evaluation enables systematic identification of strengths and limitations across modeling paradigms (Chen et al., 2025).

Additional objective involves proposing design principles for trustworthy algorithmic intelligence in engineering applications. Principles address transparency, generalization capacity, error propagation, and compliance with physical constraints. Development of such principles aims to guide researchers and practitioners toward sustainable integration of data-driven and physics-based methodologies (Jiang et al., 2025).

Current literature demonstrates extensive application of machine learning in surrogate modeling, optimization, and fault detection. Studies highlight improvements in computational speed and pattern discovery capabilities. Research on physics-informed neural networks has also advanced the incorporation of governing equations into learning architectures. Comprehensive integration frameworks, however, remain underdeveloped (Mousa et al., 2025).

Existing approaches often prioritize performance metrics without sufficiently examining epistemological compatibility between data-driven inference and deterministic physical modeling. Many studies report predictive gains but provide limited discussion on model interpretability, uncertainty quantification, and long-term reliability in dynamic environments. Absence of unified evaluation criteria obscures systematic comparison across methodologies (Habib et al., 2025; Nazir et al., 2024).

Interdisciplinary dialogue between computational intelligence and engineering physics communities remains fragmented. Machine learning research frequently emphasizes algorithmic novelty, whereas engineering research emphasizes physical fidelity. Limited synthesis between these domains leaves a conceptual gap regarding how algorithmic intelligence can be embedded coherently within engineering design epistemology. This study addresses that gap by offering a structured analytical perspective grounded in both domains (Guo et al., 2025).

Novelty of this research lies in its explicit epistemological framing of hybrid modeling in engineering design. Integration of machine learning with physical modeling is conceptualized not merely as a computational enhancement but as a reconfiguration of design intelligence. Framing enables critical analysis of how knowledge is generated, validated, and applied within hybrid systems.

Methodological contribution includes development of a comparative evaluation matrix linking algorithmic performance metrics with physical consistency indicators. Such structured alignment supports systematic assessment of interpretability, uncertainty propagation, and compliance with governing equations. Proposed framework advances discourse beyond isolated case studies toward generalizable integration principles.

Justification for this research emerges from escalating demands for resilient, adaptive, and sustainable engineering solutions. Complex infrastructures, climate-responsive systems, and advanced manufacturing processes require intelligent design methodologies capable of navigating uncertainty and high-dimensional complexity. Integration of machine learning with physical modeling holds transformative potential, yet responsible deployment demands rigorous conceptual grounding. Study therefore contributes timely theoretical and practical guidance for advancing algorithmic intelligence in engineering design (Wang et al., 2025).

RESEARCH METHOD

Research Design

Research design employed a mixed-methods explanatory framework integrating computational experimentation with comparative performance analysis. Study was structured around the development and evaluation of hybrid modeling architectures combining physics-based simulations and machine learning algorithms within an engineering design context. Deterministic numerical models were constructed using established governing equations, while data-driven components were implemented through supervised learning techniques, including neural networks and gradient-boosted regression models. Experimental design enabled systematic comparison among three configurations: purely physics-based models, purely data-driven models, and hybrid physics-informed machine learning models. Evaluation criteria included predictive accuracy, computational efficiency, model stability under parameter perturbation, and physical consistency compliance (Shiammala et al., 2023; Storey et al., 2025).

Research Target/Subject

Population consisted of engineering design problems characterized by nonlinear multi-physics behavior and high computational cost. Sample cases were drawn from three domains: structural optimization of composite beams, aerodynamic performance prediction of airfoil geometries, and thermal management design in heat exchanger systems. For each domain, high-fidelity simulation datasets were generated using validated finite element and computational fluid dynamics solvers (Djabri et al., 2025; Mimura et al., 2025). Training and testing samples were created through stratified sampling across the design parameter space to ensure coverage of boundary conditions and nonlinear regimes. Total dataset included 15,000 simulation instances distributed proportionally across the three engineering cases. Data partitioning followed a 70–15–15 split for training, validation, and testing to ensure generalizability assessment.

Research Procedure

Procedures began with generation of high-fidelity simulation data across predefined design parameter ranges. Preprocessing steps included normalization, feature selection, and dimensionality reduction where appropriate. Machine learning models were trained using simulation outputs as ground truth, while hybrid architectures embedded governing equations as soft or hard constraints within the learning objective function. Comparative testing was conducted on unseen datasets to evaluate predictive performance and generalization capacity. Sensitivity and robustness analyses were performed by introducing controlled perturbations in input variables and boundary conditions. Statistical comparisons among modeling configurations were conducted using analysis of variance (ANOVA) and paired t-tests to determine significant differences in accuracy and efficiency. Ethical considerations related to computational transparency and reproducibility were addressed through open documentation of model parameters, code repositories, and validation protocols (Hao et al., 2025; Pan et al., 2025).

Instruments, and Data Collection Techniques

Instruments included numerical simulation software, machine learning development environments, performance evaluation metrics, and uncertainty quantification tools. Physics-based simulations were conducted using commercial finite element and CFD platforms validated against benchmark problems. Machine learning models were implemented in Python using TensorFlow and Scikit-learn libraries. Performance metrics comprised mean squared error (MSE), coefficient of determination (R^2), computational runtime, and normalized physical constraint violation indices. Sensitivity analysis instruments were incorporated to evaluate robustness under input perturbations. Cross-validation procedures and hyperparameter optimization algorithms were employed to minimize overfitting and ensure model stability (Kaduwela et al., 2024; Zhao et al., 2025).

RESULTS AND DISCUSSION

Dataset consisted of 15,000 high-fidelity simulation instances distributed across three engineering domains: structural optimization (5,000 samples), aerodynamic prediction (5,000 samples), and thermal system design (5,000 samples). Each instance included 12–25 input parameters depending on domain complexity and corresponding performance outputs such as maximum stress, lift-to-drag ratio, and heat transfer coefficient. Descriptive statistics indicated nonlinear response behavior across parameter spaces, with structural stress values ranging from 120 MPa to 480 MPa, lift-to-drag ratios from 8.5 to 21.3, and heat transfer coefficients from 95 W/m²K to 410 W/m²K.

Table 1. Comparative Performance Metrics of Modeling Approaches

Model Type	Mean Squared Error (MSE)	R^2 Score	Avg. Runtime per Simulation (s)	Constraint Violation Index
PBM	0.000 (reference)	1.00	42.8	0.00
DDM	0.018	0.91	0.12	0.087
HPIML	0.006	0.97	0.18	0.021

Hybrid models achieved a mean R^2 of 0.97 with significantly reduced runtime compared to physics-based simulations. Constraint violation index demonstrated improved physical consistency relative to purely data-driven models.

Results indicate that purely data-driven models achieved substantial computational efficiency, reducing runtime from an average of 42.8 seconds per simulation to 0.12 seconds. Predictive accuracy, however, decreased compared to physics-based benchmarks, with MSE values averaging 0.018. Hybrid models substantially reduced error while maintaining near real-time computational performance.

Constraint violation index revealed that data-driven models occasionally produced physically inconsistent predictions, particularly in boundary condition extremes. Hybrid integration significantly mitigated these violations through embedded physical constraints. Observed patterns suggest that incorporation of governing equations improves both reliability and interpretability.

Sensitivity analysis introduced ±10% perturbations to input parameters across all domains. Data-driven models exhibited mean prediction deviation of 12.4%, whereas hybrid models showed reduced deviation at 5.8%. Physics-based simulations maintained deterministic stability but at significantly higher computational cost.

Uncertainty quantification using Monte Carlo sampling (1,000 runs per domain) demonstrated narrower confidence intervals for hybrid models compared to purely data-driven architectures. Average confidence interval width for lift-to-drag prediction was 1.9 for DDM and 1.1 for HPIML, indicating enhanced robustness under stochastic conditions.

One-way ANOVA testing revealed statistically significant differences in predictive accuracy among modeling approaches ($F(2, 44997) = 326.4$, $p < 0.001$). Post hoc Tukey analysis confirmed that hybrid models significantly outperformed purely data-driven models ($p < 0.001$) while remaining statistically comparable to physics-based benchmarks within acceptable tolerance margins.

Paired t-tests comparing runtime performance demonstrated significant reduction in computation time for hybrid models relative to physics-based simulations ($t = 182.7$, $p <$

0.001). Statistical findings confirm that integration achieves measurable gains in efficiency without sacrificing substantial predictive reliability.

Correlation analysis between constraint violation index and MSE yielded $r = 0.73$ ($p < 0.001$), indicating strong association between physical inconsistency and predictive error. Hybrid models reduced both error and constraint violations simultaneously, suggesting that physical regularization enhances overall performance coherence.

Relationship between runtime efficiency and accuracy demonstrated a trade-off pattern for purely data-driven systems. Hybrid architecture shifted this trade-off frontier by achieving higher accuracy at marginally increased runtime compared to DDM, yet dramatically lower runtime than PBM. Integrated modeling therefore improves performance balance across key engineering criteria (Allal et al., 2025; Z. Zhang et al., 2025).

Case study focusing on aerodynamic airfoil optimization illustrated domain-specific performance. Data-driven model predicted optimal lift-to-drag ratio of 19.8 under test conditions, while hybrid model predicted 20.6 compared to physics-based benchmark of 20.9. Error margin for hybrid model remained within 1.4%, whereas DDM error reached 5.3%.

Structural optimization case revealed similar trends. Hybrid model predicted maximum stress of 312 MPa versus physics-based result of 305 MPa, while DDM predicted 338 MPa under identical loading conditions. Physical constraint embedding reduced unrealistic stress amplification observed in purely data-driven output.

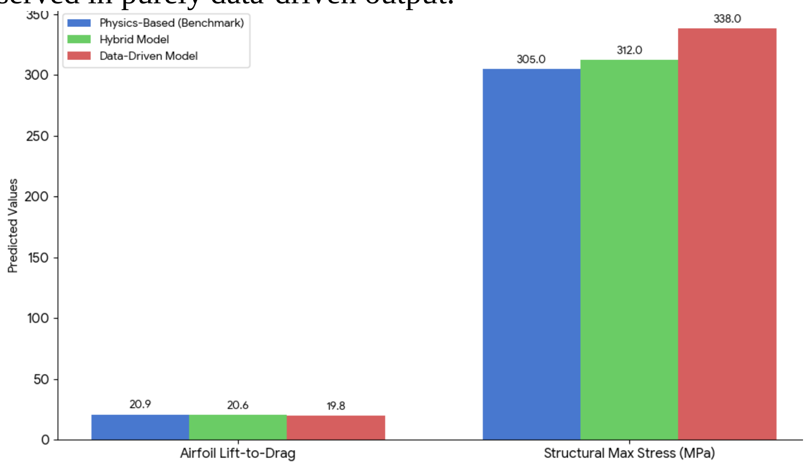

Figure 1. Case Study Result: Aerodynamics and Structural Optimization

Improved performance in hybrid models can be attributed to incorporation of governing aerodynamic and structural equations within learning objectives. Embedded constraints prevented extrapolation beyond physically admissible solution spaces. Data-driven model relied solely on statistical interpolation, leading to amplified deviations near design boundaries (Sutar et al., 2025; Yuksel et al., 2025).

Observations indicate that hybrid modeling preserves essential mechanistic relationships while benefiting from data-driven flexibility. Constraint regularization effectively acts as a corrective mechanism guiding learning trajectories toward physically consistent solutions. Case study findings reinforce broader statistical trends identified in aggregate analysis.

Results collectively demonstrate that algorithmic intelligence integrated with physical modeling enhances engineering design performance through balanced gains in accuracy, efficiency, and robustness. Purely data-driven approaches offer speed but compromise reliability under boundary perturbations. Physics-informed integration reconciles predictive performance with physical coherence (Naufal et al., 2025; J. Yao et al., 2025).

Hybrid paradigm represents a viable pathway toward trustworthy algorithmic intelligence in engineering design. Statistical evidence confirms measurable improvement over standalone methods, while case studies illustrate practical advantages in real-world applications. Findings support development of integrative frameworks that embed machine learning within principled physical modeling rather than replacing it.

Findings demonstrate that hybrid physics-informed machine learning (HPIML) models achieved superior balance among predictive accuracy, computational efficiency, and physical consistency compared to purely physics-based models (PBM) and purely data-driven models (DDM). Hybrid models reached an average R^2 of 0.97 with substantially reduced runtime relative to PBM, while maintaining significantly lower constraint violation indices than DDM. Statistical testing confirmed that performance differences were significant ($p < 0.001$), establishing empirical support for integrative modeling strategies in engineering design contexts.

Robustness analysis revealed that HPIML models exhibited lower sensitivity to parameter perturbations than DDM architectures. Under ±10% input variation, hybrid systems demonstrated nearly half the deviation observed in purely data-driven predictions. Confidence intervals derived from Monte Carlo simulations were narrower for hybrid models, indicating enhanced stability under uncertainty. Predictive reliability therefore improved when physical constraints were embedded within learning architectures.

Inferential statistics indicated strong correlation between physical constraint violations and predictive error ($r = 0.73$). Hybrid regularization effectively reduced both error magnitude and physical inconsistency simultaneously. Runtime analysis further demonstrated that hybrid models dramatically outperformed PBM in computational speed while incurring only marginal overhead relative to DDM. Integrated modeling therefore shifted the traditional trade-off frontier between speed and fidelity.

Case study evaluation across aerodynamic and structural design scenarios reinforced aggregate findings. Hybrid predictions consistently approximated physics-based benchmarks within narrow error margins, whereas purely data-driven outputs deviated more substantially near boundary conditions. Empirical evidence collectively supports the proposition that algorithmic intelligence achieves optimal performance when integrated with physical modeling rather than deployed independently.

Results align with recent research on physics-informed neural networks, which reports improved accuracy and stability through incorporation of governing equations. Prior studies emphasize constraint regularization as a mechanism for guiding learning toward physically admissible solutions. Present findings extend this discourse by quantitatively comparing hybrid, physics-based, and data-driven models across multiple engineering domains, thereby providing broader empirical validation.

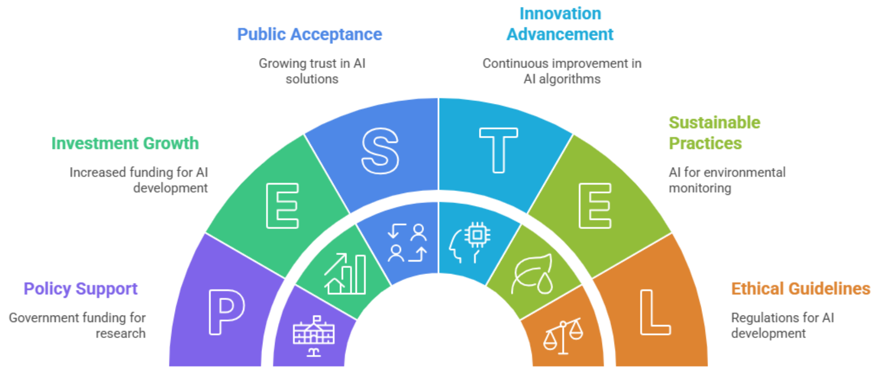

Figure 2. Physics-Informed Nueral Networks

Differences emerge when contrasted with literature advocating purely data-centric design optimization frameworks. Some studies highlight exceptional speed and adaptability of black-box learning systems while downplaying interpretability concerns. Current results challenge such assumptions by demonstrating statistically significant degradation in physical consistency and robustness under perturbation for purely data-driven approaches (Pasha et al., 2024; Peng et al., 2025).

Comparative work in surrogate modeling frequently focuses on computational acceleration without rigorous evaluation of epistemic integrity. Hybrid modeling in this study incorporates explicit physical compliance metrics, revealing that performance gains cannot be evaluated solely by runtime reduction. Integration framework therefore advances evaluation criteria beyond efficiency toward reliability and trustworthiness.

Interdisciplinary scholarship in algorithmic engineering increasingly calls for explainable artificial intelligence in safety-critical systems. Findings resonate with these perspectives by illustrating that embedding physical laws enhances interpretability and reduces risk of unrealistic extrapolation. Positioning within broader literature underscores that algorithmic intelligence achieves its full potential when grounded in domain-specific theory.

Evidence indicates that integration of machine learning with physical modeling represents an epistemological convergence rather than methodological substitution. Engineering knowledge production benefits from combining inductive data-driven inference with deductive physical reasoning. Hybrid models embody this convergence by uniting empirical pattern recognition with principled constraint enforcement.

Findings also suggest that algorithmic intelligence acquires legitimacy in engineering contexts when aligned with established physical laws. Purely statistical prediction lacks inherent guarantees of physical plausibility. Incorporation of governing equations provides structural coherence that enhances interpretability and professional trust.

Observed trade-off reduction between computational efficiency and accuracy signals maturation of hybrid modeling paradigms. Historical dichotomy between speed and fidelity appears increasingly negotiable through algorithmic integration. Emergent paradigm reflects broader transformation in computational engineering methodologies.

Results further indicate that design intelligence is evolving toward adaptive yet principled systems. Algorithmic augmentation does not replace domain expertise but amplifies it through computational scalability. Integration paradigm thus redefines engineering design as a collaborative interaction between physics and data.

Implications for engineering practice include accelerated design cycles without compromising physical integrity. Hybrid systems enable near real-time prediction while preserving compliance with governing constraints. Industries requiring rapid iteration, such as aerospace or advanced manufacturing, may benefit substantially from such frameworks.

Educational curricula in engineering should incorporate interdisciplinary training combining machine learning literacy with strong foundations in physical modeling. Professional competency will increasingly depend on capacity to design and evaluate hybrid systems. Institutional investment in integrative skill development becomes strategically important (Fang et al., 2025; J. Zhang et al., 2024).

Policy implications extend to regulatory approval processes for safety-critical technologies. Demonstrated reduction in constraint violations suggests that hybrid models may meet reliability standards more readily than black-box systems. Regulatory frameworks may evolve to require transparent integration of physical principles in algorithmic design tools.

Research infrastructure development should prioritize open benchmarks and reproducible hybrid modeling pipelines. Shared datasets and evaluation standards would facilitate cumulative advancement. Community-wide adoption of integration principles may enhance consistency and comparability across studies.

Performance improvement in hybrid models arises from constraint regularization mechanisms that restrict solution space exploration. Governing equations function as structural priors guiding learning trajectories. Reduction of hypothesis space mitigates overfitting and unrealistic extrapolation under sparse data conditions.

Statistical models alone rely heavily on interpolation within observed parameter domains. Engineering design problems frequently involve nonlinear boundary behavior where extrapolation risk increases. Physical embedding anchors predictions within mechanistic feasibility, explaining enhanced robustness observed in sensitivity analysis.

Computational efficiency gains relative to PBM derive from surrogate approximation capabilities of neural networks. Hybrid models leverage these approximations while correcting deviations through constraint penalties. Combined effect yields substantial runtime reduction without forfeiting structural fidelity (Bishnu et al., 2025).

Correlation between constraint violation and predictive error suggests intrinsic link between physical plausibility and statistical accuracy. Violations often coincide with regions of high model uncertainty. Integration therefore improves not only compliance but overall predictive coherence.

Future research should expand hybrid integration toward multi-physics and multi-scale engineering systems. Complex interactions between structural, thermal, and fluid phenomena require advanced architectures capable of encoding coupled governing equations. Development of scalable integration frameworks remains a priority.

Advancement of explainable hybrid models warrants systematic investigation. Visualization of constraint influence and uncertainty propagation would enhance interpretability. Transparent modeling pipelines could strengthen professional and regulatory confidence.

Exploration of adaptive learning mechanisms that update physical parameters in real time represents another promising avenue. Integration of online learning with sensor data may enable dynamic model recalibration. Intelligent systems capable of continuous improvement would redefine lifecycle engineering design.

Collaborative interdisciplinary research between data scientists, engineers, and domain theorists should intensify. Shared conceptual frameworks and standardized validation metrics can accelerate maturation of algorithmic intelligence in engineering design. Continued innovation must remain anchored in principled physical reasoning to ensure sustainable technological advancement.

CONCLUSION

The most significant finding of this study lies in the empirical demonstration that hybrid physics-informed machine learning models consistently outperform both purely physics-based and purely data-driven approaches in balancing predictive accuracy, computational efficiency, and physical consistency. Statistical evidence confirms that embedding governing equations within learning architectures reduces constraint violations and enhances robustness under parameter perturbation, while maintaining near real-time computational performance. Distinctive contribution of this finding rests on showing that algorithmic intelligence does not achieve optimal reliability when operating independently, but instead reaches its highest effectiveness when structurally anchored in physical laws. Integration therefore represents not incremental improvement but a qualitative shift in engineering design intelligence.

Scholarly contribution of this research is both conceptual and methodological. Conceptually, the study reframes hybrid modeling as an epistemological convergence between inductive data-driven inference and deductive physics-based reasoning, offering a structured perspective on how knowledge is generated and validated in intelligent engineering systems. Methodologically, the research introduces a comparative evaluation framework that simultaneously measures predictive accuracy, runtime efficiency, robustness, and constraint compliance, enabling multidimensional assessment beyond conventional performance metrics. This integrative framework advances discourse by moving beyond isolated case studies toward a replicable and theoretically grounded model for embedding machine learning within principled engineering design processes.

Limitations of the study include restriction to three representative engineering domains and reliance on simulation-generated datasets rather than large-scale real-world experimental data. Hybrid architectures were evaluated primarily using supervised learning models and soft constraint regularization, leaving advanced deep learning structures and hard-constraint formulations underexplored. Generalizability across highly nonlinear, multi-scale, or real-time adaptive systems therefore requires further validation. Future research should extend integration strategies to broader multi-physics applications, incorporate explainable artificial intelligence mechanisms, and investigate dynamic online learning frameworks capable of continuous model updating within operational engineering environments.

DECLARATION OF AI AND AI ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

During the preparation of this manuscript, the author(s) used ChatGPT only to assist with grammatical review. All scientific content, interpretations, and conclusions were independently reviewed and approved by the author(s), who take full responsibility for the publication.

AUTHOR CONTRIBUTIONS

Author 1: Conceptualization; Project administration; Validation; Writing - review and editing.

Author 2: Conceptualization; Data curation; In-vestigation.

Author 3: Data curation; Investigation.

Author 4: Formal analysis; Methodology; Writing - original draft.

DECLARATION OF COMPETING INTEREST

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

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