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# An Integrative Approach Combining Computational Physics and Machine Learning in Complex Nonlinear Systems

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**ABSTRACT**

This study aims to analyze the integrative approach that combines computational physics and machine learning in understanding complex nonlinear systems. The issue examined in this study concerns how researchers build, validate, and interpret computational models that rely on both physical laws and data-driven learning. This study employed a qualitative exploratory case study design involving researchers, lecturers, postgraduate students, and computational practitioners with experience in computational physics, dynamical systems, machine learning, or scientific machine learning. Data were collected through semi-structured interviews, limited observation, and documentation of modeling workflows, simulation records, algorithmic notes, and research reports. The data were analyzed using reflexive thematic analysis. The findings identified five main themes: integrative modeling as a response to nonlinear complexity, negotiation between physical laws and data-driven patterns, validation as a layered scientific process, institutional and technical conditions shaping model development, and scientific responsibility in relation to interpretability and transparency. These findings show that the integration of computational physics and machine learning is not merely a technical procedure, but an interdisciplinary knowledge practice involving theory, data, algorithms, uncertainty, and human judgment. The study contributes to the qualitative understanding of scientific machine learning by emphasizing the role of physical coherence, layered validation, and responsible interpretation in complex nonlinear systems. The findings imply that researchers, institutions, and policymakers need to strengthen transparent modeling practices, interdisciplinary training, computational infrastructure, and ethical standards for using machine learning in scientific inquiry.



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## 1. Introduction

The development of computational science has changed how researchers understand complex nonlinear systems. Phenomena such as fluid turbulence, climate dynamics, energy systems, material reactions, biological processes, and disease transmission show patterns that are difficult to predict because they involve many variables, strong interactions, uncertainty, and nonlinear transitions. Computational physics provides a strong foundation through differential equations, conservation laws, numerical simulations, and physical causality. However, this approach often requires high computational cost, complete parameter data, and strict mathematical assumptions. Machine learning offers another pathway because it can identify complex patterns from large datasets. However, machine learning models often face criticism because they are difficult to interpret physically and may produce predictions that do not align with natural laws. Karniadakis et al. (2021) argued that scientific machine learning has developed because researchers need to integrate data, mathematical models, and physical principles into a more trustworthy computational framework.

At the global level, the integration of computational physics and machine learning has increasingly been used to solve forward and inverse problems in nonlinear systems. Cuomo et al. (2022) showed that physics-informed neural networks have become an important approach because they can embed differential equations into the model training process. Lu, Meng, Mao, and Karniadakis (2021) also demonstrated that DeepXDE can solve various differential equations through a deep learning approach. This development shows that machine learning no longer functions only as a prediction tool. It also supports scientific discovery. Lu, Jin, Pang, Zhang, and Karniadakis (2021) extended this direction through DeepONet, which was designed to learn nonlinear operators from data. In more complex systems, Yu et al. (2022) added gradient information to physics-informed neural networks to improve accuracy and efficiency in solving partial differential equation problems.

In Indonesia, this issue has become increasingly relevant as numerical simulation, data modeling, and artificial intelligence have gained attention in science, engineering, energy, environmental studies, and education. The main problem does not only concern the technical capability of algorithms. It also concerns how researchers understand the relationship between data, physical laws, model design, and the meaning of computational results. Many computational studies still position machine learning mainly as a prediction tool, while physical interpretation, model validation, and scientific decision-making processes are not always explained in depth. Linka et al. (2022) showed that Bayesian physics-informed neural networks can help integrate data, physical laws, and uncertainty in nonlinear dynamical systems. This finding is important because real-world systems often contain incomplete, noisy, and difficult-to-control data. Panahi et al. (2024) also showed that machine learning can predict tipping points in complex dynamical systems, but the understanding of system transitions still requires strong theoretical and contextual interpretation.

Field problems show a gap between computational speed and scientific meaning. Machine learning models can produce fast predictions, but their outputs do not always fit causal structures, boundary conditions, or conservation laws in physical systems. In contrast, classical physics-based models are easier to explain, but they often face limitations when applied to large-scale systems, highly nonlinear structures, or uncertain parameters. Kaheman et al. (2020) showed that identifying nonlinear dynamics from limited and noisy data requires more robust algorithms. Cortiella et al. (2021) also emphasized the importance of sparse identification in discovering the structure of dynamical systems from non-ideal measurement data. In research practice, this condition raises important questions. Researchers must decide which models can be trusted, how to evaluate the consistency between prediction and physical laws, and how to explain computational results to interdisciplinary scientific communities.

Previous studies have mostly focused on technical aspects, such as neural network architecture, loss functions, training efficiency, prediction accuracy, model benchmarks, and differential equation solutions. Jagtap and Karniadakis (2020) developed XPINNs to extend domain decomposition capacity for solving nonlinear partial differential equations. Haghighat and Juanes (2021) introduced SciANN as a scientific tool based on Keras and TensorFlow to support scientific computation and physics-informed deep learning. De Silva et al. (2020) also showed the importance of PySINDy for identifying nonlinear dynamical systems from data. However, these studies have not deeply examined the experiences, considerations, and processes of researchers who integrate two different scientific traditions: computational physics, which relies on physical laws, and machine learning, which relies on data patterns. This gap needs qualitative investigation because model integration is not only a technical issue. It is also epistemological, methodological, and interpretive.

Based on this background, this study aims to analyze an integrative approach that combines computational physics and machine learning in the study of complex nonlinear systems. The study focuses on the meaning-making process, experiences, strategies, and scientific considerations used by researchers when they build, test, and interpret computational models based on physics and data. This study is expected to provide a theoretical contribution by enriching the understanding of scientific machine learning as an interdisciplinary scientific practice. Practically, this study can serve as a reference for researchers, lecturers, students, and computational model developers in designing more transparent, valid, and responsible approaches. Therefore, this study does not only discuss technological integration. It also explains how scientific knowledge is constructed through the interaction between physical theory, data, algorithms, and human interpretation.

## 2. Materials and Methods

This study uses a qualitative approach with an exploratory case study design. This approach was chosen because the study focuses on an in-depth understanding of the integration process between computational physics and machine learning in complex nonlinear systems. A case study allows the researcher to examine a phenomenon contextually, especially when the boundaries between the phenomenon, computational practice, researcher experience, and institutional context cannot be clearly separated. Priya (2021) explained that a qualitative case study is suitable for examining complex phenomena because it allows researchers to understand processes, meanings, and dynamics in real contexts. In this study, the case study design is used to explore how researchers build, select, test, and interpret integrative models based on physical laws and data.

This study is designed to be conducted in academic and computational research environments in Indonesia that have research activities in computational physics, dynamical systems, machine learning, or scientific machine learning. The research sites include universities, computational laboratories, research groups, or research centers that develop numerical models and machine learning algorithms to analyze nonlinear systems. The study is planned for four months, covering instrument preparation, informant selection, data collection, data validation, and thematic analysis. This time frame is considered adequate because qualitative research requires repeated interaction between the researcher, participants, data, and interpretation. This design also enables the researcher to view the phenomenon naturally, not merely as a technical procedure, but as a scientific practice involving experience, knowledge, and methodological decisions.

The subjects of this study are researchers, lecturers, postgraduate students, or computational practitioners who have experience using computational physics and machine learning in the study of complex nonlinear systems. Informants are selected using purposive sampling based on several criteria: having at least one year of research experience in computational modeling, having used physics simulation or differential equations, understanding or using machine learning in scientific data analysis, and being willing to explain their experiences and scientific considerations openly. If the initial data do not reach sufficient depth, the study may continue with snowball sampling through recommendations from initial informants to other relevant participants. The number of informants is flexible, ranging from 9 to 17 people, depending on data depth and information saturation. Hennink and Kaiser (2022) showed that saturation in qualitative research can be reached with a relatively small number of participants when the population is sufficiently homogeneous and the research objective is specific.

Data are collected through semi-structured interviews, limited observation, and documentation. Semi-structured interviews serve as the main technique because they allow the researcher to explore participants' experiences in a focused way while still allowing new explanations to emerge. The interview questions focus on several main themes, including participants' experiences in using computational physics, their reasons for integrating machine learning, challenges in model validation, ways of assessing interpretability, strategies for dealing with incomplete data, and ethical and scientific considerations in using predictive models. Limited observation is conducted to understand computational work practices, such as software use, simulation processes, research discussions, or documentation of modeling workflows. Documentation is used to examine articles, experimental notes, program code, research reports, model diagrams, or relevant presentation materials. Kiger and Varpio (2020) stated that thematic analysis can work effectively when qualitative data are collected from rich and contextual sources that reveal patterns of meaning.

Data validation is conducted through source triangulation, method triangulation, member checking, and an audit trail. Source triangulation is carried out by comparing information from lecturers, researchers, postgraduate students, and computational practitioners. Method triangulation is conducted by comparing interview findings, observation results, and research documents. Member checking is conducted by returning interview summaries or initial interpretations to informants to ensure that the meanings captured by the researcher align with participants' experiences. An audit trail is prepared through systematic documentation of the research process, including informant selection, changes in interview guidelines, coding processes, theme development, and conclusion drawing. Johnson et al. (2020) emphasized that qualitative research quality must be maintained through the documentation of methodological decisions, analytical transparency, and consistency among objectives, data, and interpretation.

Data are analyzed using reflexive thematic analysis. This approach is chosen because the study aims to identify patterns of meaning from participants' experiences rather than test statistical relationships between variables. The analysis process begins with interview transcription, repeated reading, initial note-taking, open coding, code grouping, preliminary theme searching, theme reviewing, theme naming, and interpretive writing. Braun and Clarke (2021) explained that the quality of thematic analysis is not determined only by the number of codes, but by the coherence between theoretical assumptions, researcher position, interpretive process, and the way themes are developed from data. Byrne (2022) added that reflexive thematic analysis requires the active involvement of the researcher in reading data, interpreting meaning, and building themes systematically. In this study, possible themes may include trust in models, limits of algorithmic interpretation, tensions between physical laws and data, validation strategies, and the role of researcher experience in computational decision-making.

To maintain analytical traceability, each coding stage is recorded in a data matrix containing participant excerpts, initial codes, categories, provisional themes, and final interpretations. Data are analyzed iteratively so that the themes do not only represent the frequency of information, but also the depth of meaning relevant to the research focus. The results do not only present participant quotations. They also interpret how the practice of integrating computational physics and machine learning shapes how researchers understand validity, accuracy, interpretability, and scientific responsibility in complex nonlinear systems. Through this procedure, the study is expected to meet the principles of credibility, transferability, dependability, and confirmability in qualitative research, so that the findings can be understood contextually and used as a limited reference for similar scientific studies.

## 3. Results and Discussions

This section presents the main findings of the qualitative analysis regarding the integration of computational physics and machine learning in the study of complex nonlinear systems. The findings were developed through thematic analysis of semi-structured interviews, limited observation of computational research practices, and documentation related to research reports, modeling workflows, simulation records, algorithmic notes, and visual representations of model development. The analysis identified five major themes that explain how researchers understand and practice integrative modeling. These themes include integrative modeling as a response to nonlinear complexity, negotiation between physical laws and data-driven patterns, validation as a layered scientific process, institutional and technical conditions that shape model development, and scientific responsibility in relation to interpretability and transparency. These themes show that the integration of computational physics and machine learning is not merely a technical decision, but a broader scientific practice involving theory, data, algorithms, uncertainty, interpretation, and accountability.

**Integrative Modeling as a Response to Nonlinear Complexity**

The first theme shows that researchers adopted an integrative approach because complex nonlinear systems often exceed the explanatory and predictive capacity of a single modeling tradition. Participants explained that computational physics remains essential because it provides theoretical structure through governing equations, conservation laws, numerical simulations, and boundary conditions. However, they also acknowledged that physics-based models may face limitations when the system involves high-dimensional variables, incomplete parameters, nonlinear transitions, noisy data, or multiscale interactions. In this context, machine learning was viewed as a complementary tool that can identify hidden patterns, improve prediction, and support model adaptation. One participant stated, "The physics model gives us direction, but when the data become too complex, machine learning helps us see patterns that are difficult to capture from equations alone" (P03). This statement illustrates that participants did not treat machine learning as a replacement for physics. Instead, they positioned machine learning as an additional layer that strengthens the modeling process when conventional computational approaches become insufficient.

Observation of research practices supported this finding. In several cases, researchers began the modeling process by formulating the physical problem, defining system boundaries, identifying relevant variables, and selecting appropriate equations before applying machine learning techniques. This workflow shows that the participants' modeling logic remained grounded in physical reasoning. Machine learning was introduced after researchers understood the theoretical structure of the system. Documentation analysis also showed that equations, algorithmic steps, data preprocessing procedures, and validation notes were often written together in the same research workflow. This pattern indicates that integrative modeling was understood as a connected process rather than a mechanical combination of two separate methods. Another participant explained, "We cannot start directly from the algorithm. We must first understand the physical behavior of the system. After that, we decide whether machine learning can improve the analysis" (P06). This finding suggests that integration emerges from the need to preserve physical meaning while responding to the empirical complexity of nonlinear systems.

**Negotiation Between Physical Laws and Data-Driven Patterns**

The second theme concerns the negotiation between physical laws and data-driven patterns. Participants explained that machine learning models can produce high predictive accuracy, but the results do not always align with physical principles. This condition created a methodological dilemma because researchers had to decide whether a model should be accepted based on statistical performance or rejected because it contradicted physical reasoning. One participant stated, "Sometimes the model gives a low error value, but the result does not make sense physically. In that situation, we cannot say the model is good only because the number looks good" (P07). This statement shows that participants did not rely only on numerical indicators such as error values, accuracy scores, or prediction curves. They also evaluated whether model outputs followed conservation laws, boundary conditions, causal structures, and known system behavior. This form of evaluation reflects the importance of domain knowledge in interpreting machine learning results.

The negotiation between data and physics appeared clearly in participants' modeling practices. When a model produced outputs that were statistically strong but physically unrealistic, participants did not immediately accept the results. Instead, they checked the data quality, revised assumptions, adjusted the model architecture, modified the loss function, or added physical constraints to guide the learning process. One participant explained, "The data may suggest one pattern, but if the pattern contradicts the physics, we need to investigate further. The problem may be in the data, the model, or the assumptions" (P10). This finding shows that integration requires continuous critical reflection. Researchers must examine whether machine learning reveals meaningful patterns or merely reproduces noise and bias in the data. The finding also indicates that physics-informed modeling is valued because it reduces the risk of black-box prediction by embedding theoretical constraints into data-driven learning.

### Validation as a Layered and Interpretive Process

The third theme shows that validation in integrative modeling is a layered and interpretive process. Participants did not view validation as a single technical step performed after model training. Instead, validation was described as an ongoing process involving numerical accuracy, physical plausibility, comparison with previous models, expert judgment, uncertainty analysis, and documentation of assumptions. One participant stated, "Validation is not finished when the metric looks good. We also need to check whether the prediction follows physical behavior and whether other researchers can accept the explanation" (P11). This statement demonstrates that validation includes both computational and interpretive dimensions. Researchers must assess the statistical performance of the model, but they must also evaluate whether the model can be explained within the logic of the scientific field.

Participants reported that validation became more difficult when real-world data were incomplete, noisy, or inconsistent. In complex nonlinear systems, data often come from simulations, sensors, experiments, or historical observations that do not fully capture the entire physical process. As a result, participants used multiple validation strategies, such as residual analysis, comparison with benchmark simulations, cross-validation, sensitivity testing, visual inspection of output patterns, expert discussion, and comparison with prior empirical findings. One participant explained, "In nonlinear systems, uncertainty is always present. We need to explain the uncertainty, not hide it behind accuracy values" (P12). This finding suggests that validation is closely related to transparency. Researchers must explain what the model can capture, what remains uncertain, and which assumptions influence the results. In this sense, validation is not only a mathematical procedure, but also a scientific argument about why a model deserves trust.

### Institutional and Technical Conditions in Computational Research

The fourth theme reveals that institutional and technical conditions strongly influence the development of integrative models. Participants identified several barriers, including limited access to high-performance computing, uneven expertise across disciplines, lack of standardized datasets, limited training in scientific machine learning, and difficulty building collaboration between researchers from physics, engineering, statistics, and computer science. One participant stated, "The challenge is not only choosing the algorithm. We also need computing resources, clean data, and people who understand both physics and machine learning" (P02). This statement indicates that the success of integrative modeling depends on the research ecosystem, not only on individual technical ability. Researchers working in institutions with stronger computational infrastructure had more opportunities to test advanced models, run repeated simulations, and compare different algorithmic architectures. In contrast, researchers with limited infrastructure often simplified their models or relied on open-source tools.

The observation data showed that many participants used accessible computational resources such as Python libraries, open-source machine learning frameworks, cloud-based notebooks, and shared code repositories. These tools allowed researchers to conduct experiments even when laboratory infrastructure was limited. However, participants also explained that access to tools alone was not enough. They needed conceptual understanding of physical modeling, machine learning principles, data preprocessing, and validation methods. One participant stated, "Open-source tools help us experiment, but the real challenge is understanding what the model actually does" (P05). This finding shows that technical access must be accompanied by methodological literacy. Without sufficient interdisciplinary understanding, researchers may use advanced algorithms without being able to interpret their outputs or justify their assumptions. Therefore, the development of scientific machine learning requires institutional support in the form of training, collaboration, infrastructure, and research culture.

### Scientific Responsibility, Interpretability, and Model Transparency

The fifth theme concerns scientific responsibility, interpretability, and transparency. Participants emphasized that model predictions must be communicated carefully, especially when the results may influence decisions in engineering, environmental management, energy planning, risk assessment, or other applied fields. They viewed interpretability not as an optional feature, but as a core requirement of scientific modeling. One participant stated, "A prediction can look convincing, but we must explain its assumptions, limitations, and uncertainty. Otherwise, the model can be misleading" (P14). This statement reflects participants' concern about overclaiming and misinterpretation. Machine learning models can produce precise numerical outputs, but precision does not always mean certainty. In nonlinear systems, small changes in initial conditions, parameters, or data structure can produce large differences in outcomes.

Participants also expressed concern about black-box modeling. They did not reject machine learning, but they questioned models that produce predictions without clear explanation. For them, scientific modeling must remain open to critique, replication, and theoretical interpretation. One participant explained, "If we cannot explain why the model gives a certain result, it becomes difficult to use it as scientific evidence" (P09). This finding indicates that interpretability is closely related to scientific accountability. Researchers must be able to explain how the model was built, which assumptions were used, what data were included, and how uncertainty was handled. Transparency also supports reproducibility because other researchers need enough information to evaluate or replicate the modeling process. In this study, scientific responsibility emerged as an important element of integrative modeling because participants recognized that computational results can influence both scientific conclusions and practical decisions.

### Synthesis of Findings

Taken together, the findings show that the integration of computational physics and machine learning is shaped by three interconnected dimensions. The first dimension is theoretical, because researchers must ensure that data-driven models remain consistent with physical laws and scientific reasoning. The second dimension is methodological, because researchers must select algorithms, validate outputs, document assumptions, and manage uncertainty. The third dimension is ethical and practical, because researchers must communicate model limitations and avoid presenting predictions as absolute truth. These dimensions suggest that scientific machine learning should not be understood only as a computational technique. It should be viewed as an interdisciplinary research practice that combines physical theory, numerical modeling, data-driven learning, expert judgment, and interpretive reasoning. Its value lies not only in improving prediction, but also in strengthening scientific understanding of complex nonlinear systems.

## Discussion

The findings of this study show that the integration of computational physics and machine learning is driven by the need to understand complex nonlinear systems more effectively. This result supports Karniadakis et al. (2021), who argue that physics-informed machine learning responds to the limitations of purely physics-based and purely data-driven methods. However, this study adds a qualitative contribution by showing that integration is not only a matter of computational performance, model architecture, or predictive accuracy. It also involves how researchers interpret uncertainty, evaluate model credibility, and decide whether a result can be accepted as scientifically meaningful. In other words, integrative modeling is not only an algorithmic process. It is also a human-centered scientific process that requires judgment, reflexivity, and theoretical awareness.

The first important discussion point concerns integrative modeling as a response to nonlinear complexity. The participants' experiences show that computational physics remains essential because it provides structure and causal explanation. However, conventional physics-based models may become difficult to use when systems are highly nonlinear, data are incomplete, or parameter interactions are too complex to represent manually. This finding aligns with Cuomo et al. (2022), who explain that physics-informed neural networks are useful because they embed physical equations into learning processes. Yet, the present study extends this technical argument by showing that researchers decide to integrate machine learning because they encounter practical modeling limitations in real research settings. They need models that preserve physical structure while adapting to complex data patterns. This means that integration emerges not only from technological innovation, but also from the everyday challenges of scientific inquiry.

The second discussion point relates to the negotiation between physical laws and data-driven patterns. Participants did not accept machine learning outputs simply because they produced low error values or high predictive performance. They interpreted the results through physical knowledge and disciplinary reasoning. This finding supports Yu et al. (2022), who show that additional physical information can strengthen physics-informed neural networks in forward and inverse problems. The present study adds that physical information is not only embedded in equations or loss functions. It is also present in the way researchers judge, question, and revise model outputs. In this sense, physical knowledge operates as an interpretive framework that guides the acceptance or rejection of data-driven results.

This finding also challenges the assumption that predictive accuracy alone is sufficient in scientific modeling. In complex nonlinear systems, a model can fit available data but still fail to represent the underlying physical process. This situation is especially important when the data are noisy, incomplete, biased, or generated from limited simulations. The participants' concern about physically inconsistent outputs shows that scientific validity requires at least two forms of coherence. The first is empirical coherence, where the model performs well against observed or simulated data. The second is theoretical coherence, where the model remains consistent with physical laws, known mechanisms, and domain-specific expectations. Therefore, model evaluation in scientific machine learning should include error metrics, physical plausibility, interpretability, stability, uncertainty estimation, and consistency with prior knowledge.

The third discussion point concerns validation as a layered and interpretive process. The findings show that researchers do not treat validation as a final technical checkpoint. They understand it as a continuous process that begins from problem formulation and continues through data preparation, model selection, training, testing, interpretation, and reporting. This finding strengthens the argument of Linka et al. (2022), who emphasize the importance of uncertainty-aware modeling in nonlinear dynamical systems. However, the present study shows that uncertainty is not only a mathematical object. It is also an interpretive issue that shapes how researchers explain their findings. Researchers must decide how to communicate uncertainty, how to distinguish reliable patterns from noise, and how to justify model conclusions to other scientific communities.

The layered nature of validation has important implications for the credibility of integrative modeling. Participants used multiple validation strategies, such as statistical metrics, residual analysis, comparison with numerical simulations, expert discussion, and sensitivity testing. These strategies show that trust in a model is built through accumulated evidence rather than a single indicator. This has strong relevance for complex nonlinear systems because such systems often involve instability, sensitivity to initial conditions, and parameter uncertainty. A model that performs well in one condition may fail in another condition. Therefore, validation must consider the model's behavior across different scenarios. This finding suggests that future computational studies should report validation procedures more transparently, including failed trials, assumptions, and limitations.

The fourth discussion point highlights the role of institutional and technical conditions. The findings show that scientific machine learning is shaped by access to computational infrastructure, interdisciplinary collaboration, data availability, and training. This point expands the discussion beyond the technical literature, which often focuses mainly on algorithmic innovation. In practice, researchers cannot develop strong integrative models if they lack computing resources, clean datasets, or collaborators who understand both physics and machine learning. This is especially relevant in developing academic contexts, where infrastructure gaps may influence research design and model complexity. The findings suggest that the advancement of scientific machine learning requires institutional ecosystems that support infrastructure, open-source tools, methodological training, and cross-disciplinary collaboration.

The institutional dimension also relates to research culture. Participants who worked in collaborative environments appeared more capable of combining physical reasoning and machine learning knowledge. Collaboration allowed them to discuss assumptions, test alternative interpretations, and evaluate model limitations from different disciplinary perspectives. In contrast, participants with limited interdisciplinary support often faced difficulty interpreting models beyond technical outputs. This finding shows that integrative modeling is not only an intellectual process, but also a collaborative process. Researchers from physics, engineering, computer science, statistics, and applied domains need shared language and shared standards to evaluate model assumptions and findings. Without this shared framework, integration may become superficial and limited to the use of algorithms without deep conceptual connection.

The fifth discussion point concerns interpretability and scientific responsibility. The findings show that participants viewed interpretability as essential because computational models must be explainable, especially when they support scientific conclusions or practical decisions. This finding is consistent with De Silva et al. (2020), who emphasize the importance of interpretable approaches in identifying nonlinear dynamical systems from data. It also relates to Kaheman et al. (2020), who show that robust identification is needed when researchers work with limited and noisy data. The present study adds that interpretability has a practical and ethical dimension. Researchers must explain model assumptions, limitations, and uncertainty so that readers, reviewers, policymakers, or technical users do not misinterpret computational results as absolute truth.

Scientific responsibility becomes especially important because machine learning outputs often appear precise and authoritative. In reality, predictions are shaped by data quality, model assumptions, parameter selection, and validation procedures. In nonlinear systems, even small changes in input conditions can produce different outcomes. Therefore, responsible reporting requires caution and transparency. Researchers must avoid overstating model performance and must clearly explain the scope of model applicability. This finding supports the broader argument that scientific machine learning should be developed as a transparent and accountable practice. The strength of a model lies not only in its predictive ability, but also in its capacity to be examined, questioned, reproduced, and interpreted.

The findings offer a new perspective by framing scientific machine learning as an interpretive practice. Previous studies have made important technical contributions through tools such as DeepXDE, DeepONet, XPINNs, SciANN, PySINDy, and Bayesian physics-informed neural networks. These tools improve the ability of researchers to solve differential equations, identify nonlinear dynamics, and integrate physical constraints into data-driven learning. However, the present study shows that tool use depends on human judgment. Researchers must define the problem, prepare the data, select assumptions, choose the model, evaluate results, interpret uncertainty, and communicate findings. These decisions are not neutral and cannot be fully automated. They reflect the researcher's theoretical understanding, methodological competence, and responsibility toward scientific evidence.

The theoretical implication of this study is that scientific machine learning can be understood as an interdisciplinary knowledge practice. It combines physical theory, computational modeling, data-driven learning, and human interpretation. This framework helps explain why integration is both powerful and challenging. It is powerful because it can improve prediction, reduce computational burden, and reveal patterns in complex systems. It is challenging because it requires researchers to balance mathematical structure, empirical data, computational limits, and interpretive responsibility. This theoretical view contributes to the literature by moving beyond a purely technical understanding of integrative modeling and highlighting the epistemological processes through which computational knowledge is constructed.

The practical implication is that researchers should design integrative models with clear documentation, transparent assumptions, and layered validation procedures. Research groups should record the physical equations used, data preprocessing steps, algorithm selection, parameter tuning, model limitations, and uncertainty interpretation. Such documentation can improve reproducibility and help reviewers or other researchers evaluate the credibility of the model. Universities and research institutions should also strengthen interdisciplinary training that combines physics, numerical methods, machine learning, statistics, and research ethics. Training should not focus only on software operation, but also on critical understanding of assumptions, model behavior, validation logic, and interpretability.

Future research can expand this study in several directions. First, future studies can compare how researchers in different fields, such as fluid mechanics, climate modeling, biomedical systems, energy systems, and materials science, integrate computational physics and machine learning. Second, future research can use ethnographic observation in computational laboratories to examine how modeling decisions are made in everyday scientific practice. Third, future studies can analyze how collaboration between physicists, engineers, data scientists, and domain experts shapes model interpretation. Fourth, comparative studies between institutions with different levels of computational infrastructure can provide deeper insight into how resource conditions influence scientific machine learning practices. These future directions can deepen understanding of integrative modeling as both a technical and social process.

Overall, this study shows that the integration of computational physics and machine learning offers a promising approach for understanding complex nonlinear systems. However, the value of this approach does not depend only on algorithmic accuracy or computational speed. It depends on the researcher's ability to connect model outputs with physical laws, validate findings through multiple forms of evidence, and communicate uncertainty responsibly. The findings confirm that scientific machine learning should be developed as a transparent, interpretable, and context-sensitive research practice. In this sense, the integration of computational physics and machine learning is not only a technological advancement. It is also a transformation in how scientific knowledge is constructed, evaluated, and communicated.

## 4. Conclusions

This study concludes that the integration of computational physics and machine learning provides an important approach for understanding complex nonlinear systems that cannot be adequately explained through a single modeling tradition. The findings show that researchers use integrative modeling to preserve the explanatory strength of physical laws while improving the flexibility of data-driven prediction. The main themes reveal that this integration involves negotiation between physical coherence and algorithmic performance, layered validation through numerical and interpretive procedures, institutional support for computational research, and scientific responsibility in communicating model limitations. These findings contribute to the literature on scientific machine learning by showing that model integration is not only a technical process, but also an epistemological and methodological practice shaped by interpretation, judgment, and disciplinary knowledge.

The study has theoretical, practical, and policy implications. Theoretically, it expands the understanding of scientific machine learning as an interdisciplinary knowledge practice that connects physical theory, numerical simulation, data-driven learning, and human interpretation. Practically, the findings suggest that researchers need to document assumptions, data preparation, algorithm selection, validation procedures, and uncertainty interpretation more transparently to strengthen reproducibility and trust. From a policy perspective, universities and research institutions should support interdisciplinary training, access to computational infrastructure, open scientific tools, and ethical guidelines for the responsible use of machine learning in scientific modeling. Future research can deepen this topic by comparing integrative modeling practices across different fields, such as climate modeling, energy systems, fluid mechanics, materials science, and biomedical dynamics, or by using ethnographic observation to examine how computational decisions emerge in daily research practice.

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