

Computational Physics as a Unifying Framework for the Natural Sciences: Bridging Disciplines through Numerical Modeling and Simulation

Muhammad Taufik^{1*}, Syahrial, A²

^{1,2} Physics Education Study Program, Department of Mathematics and Natural Sciences Education, Faculty of Teacher Training and Education, Universitas Mataram, Lombok, Indonesia.

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Corresponding Author:

Muhammad Taufik

taufikspdmsi@gmail.com

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Abstract: The collaboration between computation, theory, and experiment has been a game-changer for academia. This work considers computational physics as an integrative discipline across the natural sciences and utilizes a narrative literature review organized with a conceptual and methodological synthesis. Using peer-reviewed literature from physics, chemistry, biology, and environmental science, as well as science education, the work identifies common interdisciplinary numerical approaches, computational techniques, and algorithms used in modeling and simulation. The research demonstrates that while computational practices in research and education have evolved separately across various fields, the core techniques that have been and continue to be most important for modeling across many fields are those rooted in computational physics: finite difference, finite element, and finite volume methods. Furthermore, the synthesis demonstrates that the combination of modeling in physics and the use of machine learning and other data-driven methods, as well as the importance of computational thinking, are essential for interdisciplinary science and science education. Model formulation, discretization, numerical approximation, algorithm implementation, and data visualization are core components of a generalized computational modeling framework. While this study has provided a unified conceptual framework for multiple academic domains and interdisciplinary curriculum development, its reliance on previously established literature, coupled with the lack of primary empirical findings or simulations, is a notable limitation. This study frames the discipline of computational physics as a methodology, rather than as a field of study with clear boundaries.

Keywords: computational physics; numerical modeling; interdisciplinary science; simulation; computational thinking

Introduction

Assessing the current state of computational skills integration into physics research, education, and study in other scientific disciplines has become increasingly important in contemporary science. Following the integration of computational skills and abilities into physics research and study, the academic discipline has

evolved and branched into various subfields of study. The challenge of the modern academic environment to bridge the gap between computational skills and physics, embodying the spirit of integrating computational science as an emerging "third force" discipline, is inevitable. In response, and in recognition of the importance of integrated computational

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methodologies in solving complex problems and producing predictive models, the physical and life sciences are increasingly embracing this. The ability to simulate, model, and analyze data from each discipline individually from a knowledge of the cosmos facilitates an enhanced, interconnected understanding of phenomena.

The lack of a centralized structure and integration of methods for applying computational skills across key scientific disciplines presents a challenge. The isolated methodologies developed by each discipline have computations designed to operate in isolation. In contrast, the integration of computational physics is an interconnected system designed for this purpose. Therefore, it is proposed that collaboration and understanding of integrated computational skills across the natural sciences should be a focus.

Considering the specific methodological approach consistent with the aims of this study, a descriptive analytical review of the literature and a conceptual synthesis were chosen. Therefore, the analytical results in the following sections are the result of a methodical review and consolidation of the primary literature in the natural sciences and are not based on any original empirical research or computational simulations.

Method
Overview of the Approach

Using computational physics as an integrative methodological framework within the context of IPA research and education, this study employs a stratified descriptive analytical literature review, as well as conceptual and methodological synthesis, and this particular approach fits best with educational research wherein there are no experiments aimed at seeking outcomes and gaps, while the study focuses on the comprehension, instruction, and employment of computational techniques in the field of physics and other branches of natural sciences, along with the ways in which these techniques foster interdisciplinary integration in science education.

Research Design

With a particular focus on science education, the research design consists of a narrative literature review of a particular nature and conceptual synthesis, which, instead of focusing on the measurable outcomes of instructional interventions or learning outcomes, seeks to understand the integration and educational translation of the computational techniques derived from computational sciences in various scientific disciplines.

This design facilitates the synthesis of various sources, including research in computational physics,

modeling studies in various fields, and science education literature. This way, the research bridges computational practices of science with the teaching of science, thus providing a foundation for understanding computational practices in IPA education.

Literature Selection Strategy

The literature selection process was iterative, purposive, and focused on education. Peer-reviewed articles from journals, review papers, and papers on methodology were considered eligible if the following criteria were met:

The article in question was based on research whose focus was on computational modeling, numerical simulation, algorithmic approaches, or computational thinking. The computational approaches, however, were focused on or included physics, chemistry, biology, environmental science or integrated science education. The article contributed to the understanding of the integration of computational skills in research, teaching, curriculum development, or in educational training of teachers.

Review articles, landmark studies in methodology, and publications with a high citation index were considered more important, and so was research that made explicit the connection between computational methods and outcomes to be achieved in education or teaching, including the pedagogy of interdisciplinary science education.

Table 1 provides a summary of the reviewed studies which highlights the scope of the literature in different disciplines as well as showing how computational methods are dispersed over different fields of science.

Table 1. Distribution of Reviewed Literature by Discipline and Computational Focus

Scientific Domain	Main Computational Focus	Typical Methods Identified	Educational Relevance
Physics	Numerical modeling and simulation	FDM, FEM, FVM, spectral methods	Core foundation for computational physics instruction
Chemistry	Molecular and reaction modeling	Molecular dynamics, ML-based potentials	Application of physics-based computation in chemical systems
Biology	Complex system and data-driven modeling	ML, hybrid physics-data models	Simulation of biological processes and systems
Environmental Science	Large-scale system modeling	Numerical climate models,	Interdisciplinary modeling for

Scientific Domain	Main Computational Focus	Typical Methods Identified	Educational Relevance
Science Education	Computational thinking and modeling	statistical simulation	sustainability education
		Simulation-based learning, project-based modeling	Development of transferable computational skills

Analytical Framework

For each study integral to the research, there was a comparative interrogative framework employed with consideration to the scientific and educational elements of the studies. The analysis was cross-sectional, and the focus was on four dimensions working in unison:

The dimension of scientific modeling which includes the construction of mathematical models and the representation of phenomena in the natural world.

The dimension of computation which includes the mathematical and algorithmic formulation of techniques and the simulation of methods derived from the field of computational physics.

The dimension of education which looks at the introduction, teaching, and/or scaffolding of computational and modeling practices in science education.

The dimension of transferability which pertains to how far the strategies of learning computation and the practices of education can be used in multiple branches and levels of the same field of science and the same field of education.

This framework allowed the identification of shared computational structures while simultaneously revealing their pedagogical implications for interdisciplinary science learning.

Conceptual Synthesis

Once the comparative analysis was completed, a conceptual synthesis was completed to show the integration of findings from the scientific field and the educational field. The focus of the synthesis was on the articulation of computational physics as a methodological and pedagogical core that anchors the integration of computational modeling, simulation, and problem-solving in IPA education.

Instead of suggesting a new instructional model, the synthesis organizes existing computational practices into a coherent framework, integrating objectives of scientific inquiry, computational thinking, and science learning. This viewpoint moves computational practices in physics to the center, serving as a pivot in both disciplinary and interdisciplinary education, and thus,

facilitates the integration of curriculum and the training of teachers in the natural sciences.

Methodological Limitations

This research does not comprise new classroom interventions, innovative designs for experiential learning and newly crafted computational simulations. The work presented here is based on existing literature and thus encompasses relationships conceptually, methodologically, and pedagogically, rather than through the lens of actual learning outcomes. Still, this is in line with the purpose of this study of laying the groundwork for the integration of computational skills into the education of science and interdisciplinary research.

Result and Discussion

Conceptual and Methodological Foundations

Computational physics is the study of interconnections between theoretical physics and numerical computation. It has emphasized numerical modeling, simulation, and algorithmic modeling. It has also contributed to the development of numerical methods such as finite difference, finite element, and finite volume methods (Wang et al., 2024). These methods are also useful in other fields of natural sciences.

Computational physics has advanced alongside particle physics, statistical mechanics, and complex systems, modeling the conversion of purely theoretical ideas into constructs that can be represented and processed by a computer (Kamiscioglu, 2023).

In order to facilitate an understanding of the function of computational physics as an integrative methodological core, we present a representation (Figure 1) of the connections, within a unified computational approach, of physics, chemistry, biology, and environmental science, built from common numerical techniques and modeling methodologies.

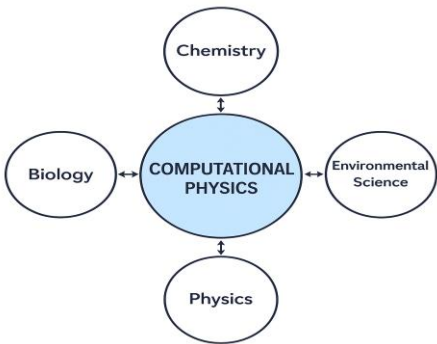


Figure 1. Conceptual framework illustrating computational physics as a unifying methodological core connecting physics, chemistry, biology, and environmental science through shared numerical methods and modeling workflows.

Fragmentation of Computational Approaches

There is a deficiency of cohesion. Computational chemistry is focused on the simulation of quickly developed strategies and molecules, (Cao & Tian, 2021); the biological field incorporates more and more machine learning (Eisenbraun et al, 2025); environmental science employs numerical methods to model the climate (Skwame et al., 2024); and physics uses grand simulations, more specifically in astrophysics and high energy physics.

In education, fragmented curricula limit the transfer of computational skills across disciplines to learners (Ningsih et al., 2024). Interdisciplinary collaboration has been proven to help them integrate ideas and foster deeper engagement (Diachenko-Bohun et al., 2023).

Computational Techniques Across Natural Sciences.

Chemistry, biology, and environmental science exhibit the use of numerical and mathematical approaches. The integration of machine learning and physics-based molecular, biological, and ecological models is gaining momentum (Gökcan & Isayev, 2021; Raja et al., 2024). Physics-informed machine learning is one of the manifestations of this convergence (Marian & Tremmel, 2023; Duignan, 2024).

Computational Thinking in Research and Learning

Computational thinking, which relies on abstraction, algorithm, and simulation, is a pillar of cross-disciplinary sciences (Yokuş & Kahramanoğlu, 2022). The use of simulation and project-based learning enables the development of transferable computational skills (Gunckel et al., 2022; Subekti et al., 2024). Teacher training programs strengthen interdisciplinary integration (Bati, 2021; Rivadeneira & Toledo, 2024).

To further illustrate this interdisciplinary approach, Figure 3 focuses on the intersection of the teaching of physics, the integration of computational methods, and the computational thinking skills and their significance for educational practice in the IPA framework in encouraging and facilitating interdisciplinary problem solving.

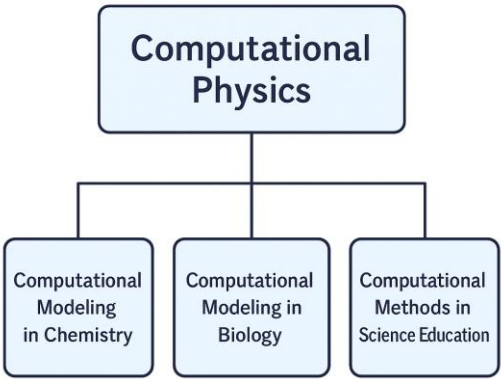


Figure 3. Integration of computational physics methodologies and computational thinking skills within science education to support interdisciplinary learning and problem-solving.

In reference to Table 3, we are integrating core computational physics concepts into educational practices to illustrate the link of computational physics to science education to foster interdisciplinary and computational thinking skills.

Table 3. Integration of Computational Physics Concepts into Science Education

Computational Physics Concept	Corresponding natural sciences Learning Activity	Learning Outcome
Numerical modeling	Simulating motion, heat, or ecosystems	Conceptual understanding of systems
Algorithmic thinking	Designing step-by-step simulations	Logical reasoning and problem-solving
Simulation	Virtual experiments and explorations	Inquiry skills and hypothesis testing
Data analysis	Interpreting simulation outputs	Scientific reasoning and interpretation
Interdisciplinary modeling	Linking physics with biology or environment	Integrated science understanding

General Computational Modeling Framework.

An extensive body of literature envisages a computational modeling workflow: model development, discretization, numerical formulation, implementation of the algorithm, and visualization of the data. The governing equations that are, in most cases, partial differential equations (PDEs) are the mathematical heart of models (Rathod, 2024). Large-scale simulations are made possible by numerical solvers and high-performance computing (Burns et al., 2020; Dang et al., 2022).

To illustrate the shared configuration of the computational practices recognized across various fields of study, Figure 2 illustrates a generalized computational modeling workflow, highlighting the

sequential and iterative character of numerical modeling in the natural sciences.

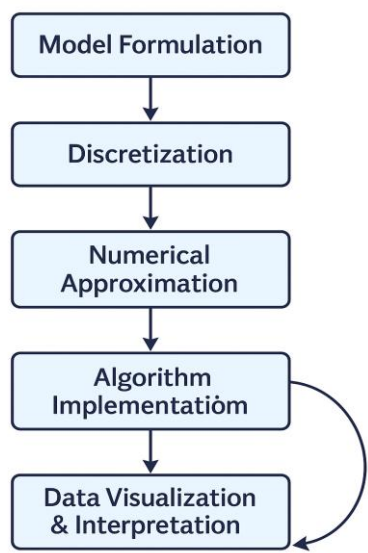


Figure 2. Generalized computational modeling workflow synthesized from the reviewed literature, illustrating common stages shared across computational practices in the natural sciences.

In regards to the steps we discussed earlier, we present, in Table 2, an outlined description of the various stages of a standard computational modeling process which orders and organizes the steps by discipline in the literature reviewed, in order to elucidate the methodological similarities of computational practices in the different fields of the natural sciences.

Table 2. Common Computational Modeling Workflow Identified Across the Natural Sciences

Modeling Stage	Description	Examples Identified	Across
Model Formulation	Translating physical or natural phenomena into mathematical models	PDEs in physics, reaction equations in chemistry	
Discretization	Converting continuous models into computable forms	FDM, FEM, FVM	
Numerical Approximation	Solving discretized equations numerically	Iterative solvers, ML-assisted solvers	
Algorithm Implementation	Coding and executing numerical solutions	Python, MATLAB, HPC frameworks	
Data Visualization	Interpreting and presenting results	Graphs, simulations, animations	

Cross-Disciplinary Applications

Identical numerical algorithms and multiphysics models are reused across physics,

chemistry, biology, and environmental science (Rajagopal et al., 2022; Wu et al., 2023). These reuses illustrate that computational physics is a transferable methodological backbone.

Educational and of Interdisciplinary Implications

Computational physics along with integrated STEM practices fosters computational literacy and the skills of collaboration and problem solving (Zohbi et al., 2022; Li et al., 2020). The use of technology and project-based methods provides an advantage in interdisciplinary education (Lee et al., 2023; Berk & Gülcü, 2024).

Limitations and of Future Directions

There are challenges in simplified frameworks and their ability in capturing nonlinear and emergent behaviors (Dhakal et al., 2025; Yusufi et al., 2025). Future work needs to include hybrid, data-driven, and physics-informed framework to improve predictive validity (Planella et al., 2022; Hou & Behdinan, 2022).

Conclusion

As computer methods become part of almost any scientific investigation, the lack of a cross-disciplinary knowledge framework grows more urgent. This study employs a systematic review of the literature and a narrative synthesis of concepts to illustrate how computational physics offers a basic methodological structure that integrates different fields of study with numerical modeling and simulation. Understanding computational physics as a methodological center allows for greater coherence in the scientific enterprise and enables true interdisciplinary and effective science.

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