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Bridging physics and biology teaching through modeling

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As the frontiers of biology become increasingly interdisciplinary, the physics education community has engaged in ongoing efforts to make physics classes more relevant to life science majors. These efforts are complicated by the many apparent differences between these fields, including the types of systems that each studies, the behavior of those systems, the kinds of measurements that each makes, and the role of mathematics in each field. Nonetheless, physics and biology are both sciences that rely on observations and measurements to construct models of the natural world. In this article, we propose that efforts to bridge the teaching of these two disciplines must emphasize shared scientific practices, particularly scientific modeling. We define modeling using language common to both disciplines and highlight how an understanding of the modeling process can help reconcile apparent differences between the teaching of physics and biology. We elaborate on how models can be used for explanatory, predictive, and functional purposes and present common models from each discipline demonstrating key modeling principles. By framing interdisciplinary teaching in the context of modeling, we aim to bridge physics and biology teaching and to equip students with modeling competencies applicable in any scientific discipline. © *2014 American Association of Physics Teachers.*
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I. INTRODUCTION

Life science students are the largest population of science majors taking physics courses at colleges and universities in the United States.[1] These students represent such a large fraction of the physics enrollment that many colleges offer separate introductory physics courses specifically for life science majors. However, the content of these physics courses is often inadequately aligned with the interests of life science students, amounting to algebra-based versions of the calculus-based courses taken by physical science and engineering majors. Recent years have seen a number of calls to improve the general state of undergraduate physics, including specific appeals to develop interdisciplinary courses that serve the needs of life science majors.[2,3]

Biology teaching in higher education is undergoing similar reconsiderations in light of new frontiers in biological research. Recent calls for transformation emphasize the need for students to understand biology from a systems perspective and to develop scientific practices. The focus on biological systems represents a new approach in biology education and provides an appropriate way to address biological complexity.[2,4] Key scientific practices for life-science students include problem solving, numeracy, communication, and modeling.[2,4,5] This grounding in biological systems and scientific practices closely aligns with the skills needed to conduct biological research and better prepares students to become professional biologists and engaged citizens.

In response to the changing needs of both physics and biology students[4] and urgent calls to develop introductory STEM courses that promote the persistence of STEM majors,[6] the physics education community is actively working to develop curricula that support the achievement and competence of life-science majors. Several universities are developing new courses in introductory physics for life science majors.[7–10] Typically, these courses focus on modifying course content, such as adding examples grounded in biology and/or teaching laboratory techniques relevant to life science majors. However, in addition to specific content, students taking these courses must also be able to reconcile the seemingly different disciplinary practices of physics and biology.

A quick glance at introductory textbooks in physics and biology can give the impression that these are very distinct kinds of science. Biology and physics typically differ in the types of systems that each studies, the behavior of those systems, the kinds of measurements that each makes, and the role of mathematics in each field. Because they focus on disciplinary content rather than scientific practices, textbooks often accentuate the differences between the disciplines. Physics textbooks[11–15] contain dozens of equations in the first few chapters alone, whereas introductory biology textbooks[16–18] contain numerous diagrams of biological systems, structures, and processes, but few equations.

While biology and physics might appear quite distinct to students, as scientific disciplines they both rely on observations and measurements to explain or to make predictions

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about the natural world. As a shared scientific practice, modeling is fundamental to both biology and physics. Models in these two disciplines serve to explain phenomena of the natural world; they make predictions that drive hypothesis generation and data collection, or they explain the function of an entity. While each discipline may prioritize different types of representations (e.g., diagrams vs mathematical equations) for building and depicting their underlying models, these differences reflect merely alternative uses of a common modeling process. Building on this foundational link between the disciplines, we propose that teaching science courses with an overarching emphasis on scientific practices, particularly modeling, will help students achieve an integrated and coherent understanding that will allow them to drive discovery in the interdisciplinary sciences.

The present paper argues that efforts to bridge biology and physics education must include an explicit emphasis on the practice of modeling. We focus on modeling because it reconciles many of the apparent differences between these two disciplines. Using canonical examples from physics and biology, we demonstrate the ubiquity of modeling by showing how biological and physical models can be framed with a relatively small set of modeling principles, constructs, and activities common to both disciplines. Using these examples, we suggest several generalizable approaches that physics educators can take to emphasize models and modeling, especially (but not exclusively) in introductory physics courses for life science students. Our theoretical approach also suggests several areas of research in the design, implementation, and evaluation of instruction in modeling. Our aim is neither a broad treatment of the nature or meaning of scientific models and modeling, nor a narrow focus on specific content that can be ported directly into introductory courses, but rather to present a framework for instructors to think about how to blend key aspects of modeling into their own physics courses.

II. DEFINING MODELS AND MODELING

The recent NRC report[3] *Adapting to a Changing World*, on the state of undergraduate physics education, highlights students' abilities to make models as essential to their development of a deep understanding of the physical sciences. Modeling has also been promoted more generally as a key practice in transforming science instruction.[4,19,20] Yet, despite the occasional use of the term "model" in our science classrooms (e.g., Bohr model, standard model of particle physics, Lotka-Volterra predator-prey model), models and modeling are rarely given explicit treatment, except in particular curricula emphasizing them.[21–23] Below, we provide operational definitions of models (products) and modeling (practices) that are broadly applicable across the sciences. By identifying the many similarities and few differences between modeling in physical and life sciences, we present a way to bridge the teaching of physics and biology through scientific practices that are fundamental to both disciplines.

A. What is a model?

Real world phenomena consist of multiple entities (e.g., organisms, atoms, energy) interacting in complex ways. Scientists gather, organize, and analyze data and information generated by these interactions. However, not all the information in the real world can be collected and interpreted simultaneously, so we use instruments to measure phenomena and filters to extract only relevant information (Fig. 1). Fundamentally, a model is a tool that simplifies the real world and allows us to interact with the idealized world in meaningful ways.[24–26] Modeling is a basic human enterprise, and we build models—simplified, conceptual constructs that help us make sense of complex and messy systems—all the time. Scientific models fulfill one or more of three functional roles: they are explanatory (e.g., using structure to explain a phenomenon or observation), predictive (e.g., of a cause or effect), and/or functional (e.g., describing processes or operations).[26,27] The process of building and using models is termed *modeling*.[19,25,26]

At a finer grain, models are driven by their objectives.[27] There may exist many equally valid models of the same system, and models often place greater value on utility than "correctness."[28] For example, the model of an atom built to make sense of the distribution of charge (Rutherford model) may be different from the model of the same system—the atom—built to make sense of the hydrogen spectrum (Bohr model). Each model, therefore, intentionally focuses on a limited set of details. Thus, every model necessarily includes assumptions—simplifying hypotheses, idealizations, or approximations.[27] In building models that necessarily simplify the real world, there is often a trade-off between simplification and robustness: a model may explain much, but be difficult to understand; or it may be understandable to many, but explain less.[29] Because simplifications are a necessary part of any model, the modeling process includes identifying both the relevant features and the level of detail needed to achieve the objectives of the model.

An essential step of any modeling process occurs when we design or use representations to communicate models with other people. Model representations foster clear thought and communication about abstract ideas and their corresponding real-world systems.[26] Within every discipline, there are standard and convenient representations that are widely used. In both physical and biological sciences, these standard representational forms include equations (with variables as symbolic notation), plain language, diagrams, pictures and animations (indicating actions or processes), and graphs. Not every equation or diagram represents a model; model representations are explanatory, predictive, or functional. In science education, the ability to represent existing and new models—and critique the models of others—becomes a key

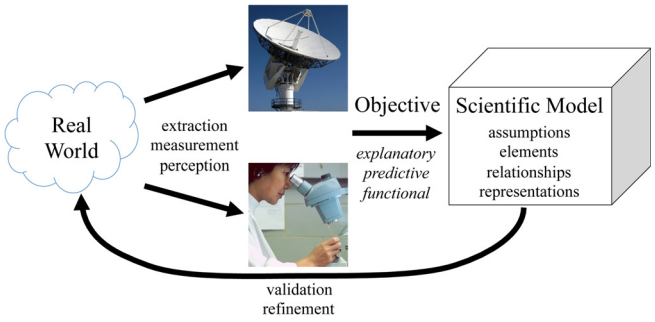


Fig. 1. Scientific models are simplified representations of natural systems, built to satisfy one or more objectives: explanation, prediction, or functionality. The modeling process is iterated when models are compared to real-world systems and validated or refined. Photo credits: NASA, <http://commons.wikimedia.org/wiki/File:KSC_radio_telescope.jpg>; National Cancer Institute, <https://visualsonline.cancer.gov/details.cfm?imageid=2172/>.

goal of mastering the practice of scientific modeling.[26,30] The ability to represent the same model system in multiple ways is also an important benchmark in students developing sophisticated conceptual understanding of physical and biological systems.[31,32]

B. What is modeling?

The process of modeling includes constructing models, making predictions, comparing predictions with measurements, refining models and explanations, and communicating model findings.[26] A testable scientific model generates predictions that can be compared with real-world observations. Predictive models allow scientists to explore hypothetical situations that are difficult, undesirable, or (especially in biology) unethical to initiate or observe. Predictive models also drive hypothesis generation in both physics and biology.

Once a scientist uses a model to make a prediction, the opportunity to compare predictions with measurements arises. The process of comparing observations to model predictions is dubbed *model testing* or *validating*.[27] When this process of comparison is iterated, it is termed *refinement*. Model refinement is not merely adding more detail to a model. It includes adding new, relevant features and removing extraneous, unnecessary features so that the model becomes more robust or better aligned with observations. Model validation is an iterative process centered on the development of ideas as the scope and sophistication of both models and observations increases.[24–27,30]

Modeling also necessarily includes the iterative process of communicating scientific ideas. As sense-making tools, models are only as useful as their representations (e.g., equations, diagrams). It is these representations that have the power to communicate an explanation, a mechanism, or a function in ways that are meaningful to others.[26,30,31]

III. WHY DO BIOLOGY AND PHYSICS SEEM SO DIFFERENT?

Models and modeling are used throughout science, and thus models in both biology and physics have the same general features: an idealized system, a model objective, assumptions, representations, limitations, refinements, and validation measures (see Tables I–III). However, the unique content of each discipline means these common features of modeling may appear distinct at first glance. We describe four perceived differences in the processes of modeling between physics and biology, arising from the nature of the systems that each studies.

Nature of models: Physics models are nearly always built to make predictions, and consequently they make extensive use of mathematical representations. Within the introductory physics course, properties like positions, velocities, forces, and energies can all be calculated as a system evolves, starting from a range of initial conditions, and this leads to a rich set of predictions. Most introductory biology courses utilize mathematical representations far less frequently.[16–18] At first glance, the lack of mathematics may give the appearance that biology models are merely functional, while physics models are predictive. However, the objective of the biological models in introductory courses is not to make precise numerical predictions, but to explain linkages between structure and function and to drive hypothesis generation.[30] In fact, many biological models make sophisticated predictions that inform experimentation.[26] Gregor Mendel developed the model of particulate inheritance—the principle that parents pass traits to their offspring via discrete particles termed genes—through his now-famous pea-plant breeding experiments. In turn, Mendel's predictive model drove future biologists to search for a substance within cells that conveyed genetic information, long before a functional or mechanistic understanding of DNA emerged.

Emphasis on different model types and objectives: Models in physics involve entities that are reduced (e.g., fundamental particles like electrons), or simplified to the point where structure is ignored (e.g., "rigid body," point mass). There are exceptions, such as with condensed matter physics, where structure and function are intimately related, but these topics are not usually part of introductory curricula. Modeling in introductory physics instead emphasizes

TABLE I. Examples and characteristics of *explanatory* models in physics (the atom) and biology (the cell). The cell image is from <http://commons.wikimedia.org/wiki/File:Celltypes.svg>, adapted from an image by the National Center for Biotechnology Information.

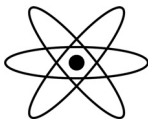
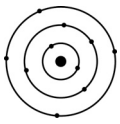
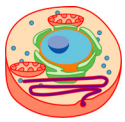
Real world	Atomic systems		Living cells
Idealized system	Rutherford atom	Bohr atom	Typical eukaryotic cell
Model objective	Explain observations of a dense, central charge	Explain the hydrogen spectrum	Describe the smallest units of life
Assumptions	Atoms have a massive, positively-charged nucleus; scattering results from interactions of α-particle and nucleus; other sources of α-particle scatter can be ignored	Stationary electrons emit no radiation; electrons occur in discrete orbits; electrons moving between orbits absorb or emit photons	All living things are composed of cells; all cells come from other cells and contain the hereditary information required to reproduce; life functions occur within (and among) cells
Representation			
Limitations	Electrons lose energy and collapse in an unstable atom	Does not accurately represent multi-electron atoms	May not represent cells with different arrangements of organelles
Refinement	Improved "plum pudding" model by proposing a massive nucleus and separate regions of charge	Improved Rutherford model by discretizing electron orbits and corresponding transition energies	Huge diversity of cells; structure/function relationship makes it impossible to represent all cells with a single model
Validation	Observation of dense, positive atomic core (Geiger, Marsden)	Observation of the spectral lines of hydrogen (Lyman, Balmer)	Observation of cells and cellular structure (Hooke, Pasteur)

Table II. Examples and characteristics of *predictive* models in physics (a body in motion) and biology (chemotaxis).

Real world	Car	Bacterial colony (10^8 members)
Idealized system	Point particle	Small collection of cells
Model objective	Predict rate or trajectory of motion	Predict the rate or trajectory of motion
Assumptions	Constant acceleration	All cells of a similar type respond to cues in the same ways
Representation	Equations, graphs	Equations, graphs
Limitations	Does not explain underlying causes of motion (e.g., how an internal combustion engine works)	Does not explain how chemotactic substances work (e.g., signal transduction); although the group's motion can be characterized probabilistically, the model cannot predict how an individual will move
Refinement	Incorporation of forces and Newton's laws	Chemotactic models that account for differences between cell types and mechanisms of cell motility may enhance predictive power.
Validation	Observation of motion	Observation of collective motion

predictive or explanatory models—the trajectory of a particle, the voltage induced by a generator, etc.—rather than functional models. Because biological systems are sufficiently complex, often the structure and function of systems are inextricably intertwined. Thus, many models in introductory biology courses begin by articulating the structure to explain the function of complex systems, such as a cell or an ecosystem, as scaffolds for understanding the mechanistic models that describe how those systems are built, organized, and maintained. For instance, to understand Mendel's discovery, students often learn about the structure and function of DNA, genes, and chromosomes.

Common representations may differ: It follows that because each discipline emphasizes different model types, model representations are different as well. Physics often begins with simple idealized systems where the objective is to explain and to make predictions. When learning about mechanics, students consider simple idealized systems where the objective is to explain and to predict the motion of objects based on interactions with their environments. Introductory physics, therefore, emphasizes graphs and equations. Because biological models vary significantly across scales, and understanding structure often precedes explaining function, biological models typically utilize multiple pictorial and diagrammatic representations for a single system. For example, biology students studying chromosomes typically work with electron microscope images; schematic, idealized diagrams of chromosome pairs during cell division; and similar representations at larger and smaller scales of organization when learning about genetics.[16]

The role of scale: Although not all physical laws are applicable at every scale (e.g., classical vs. quantum physics), this subtlety is rarely emphasized at the introductory level. The emphasis is instead on the applicability of models over a wide range of scales, such as the use of Newton's laws to model both the motion of a toy car across a student's desk and the motion of a planet around the sun. This wide applicability of physical laws enables a "bottom-up" approach in which the system of interest is reduced to fundamental basic entities and interactions that explain properties of the whole. In introductory biology, on the other hand, hierarchical and scale-dependent complexity is at the forefront. Molecules, cells, organs, organisms, populations, and ecosystems behave differently at different levels of organization, and new models are necessary at each different scale. Biological systems that students must grapple with are emergent—that is, the systems behave very differently at different spatiotemporal scales. For example, a single neuron behaves differently than a cluster of neurons, and all behaviors of the cluster cannot be predicted simply by knowing the properties of the single neuron. Properties at one scale of organization (cells) are necessary but insufficient to understand structure and function at a larger scale of organization (tissues). Because each scale range requires development of new models, the breadth of models used in an introductory biology course is large.

IV. EXAMPLES OF MODELS AND MODELING IN PHYSICS AND BIOLOGY

In this section we consider pairs of models—one each from physics and biology—that illuminate the common uses of models in each discipline. We also highlight the elements of models and modeling that are unique to each discipline. The first pair of models, the atom and the cell, represents descriptions of the building blocks of matter and life. The

Table III. Examples and characteristics of *functional* models in physics (the heat engine) and biology (cardiac function).

Real world	Heat engines	Animal heart
Idealized system	Carnot cycle	Cardiac cycle
Model objective	Describes how thermal energy is converted into mechanical energy to do work	Describes how a heart pumps blood
Assumptions	System is quasi-closed; reservoirs are infinitely large; steps are either isothermal or adiabatic	Blood is incompressible; viscosity can be ignored
Representation	*P-V* diagram of the fluid in the engine	*P-V* diagram of the fluid in a heart chamber
Limitations	Does not predict the rate of work production; does not accurately represent real engines	Describes only the process of ventricular rhythm, not its rate or total blood volume moved
Refinement	Other cycles describe real engines more accurately	Can be modified to describe two-, three-, or four-chambered hearts; Can add details of organisms' morphology
Validation	Comparison to efficiency of actual engines	Comparison to cardiac function in organisms with single-chambered hearts

second example, on the motions of cars and bacterial colonies, illustrates predictive models from physics and biology, respectively. The third pair represents functional models that elucidate the cyclic processes of energy transformation using the Carnot cycle and an idealized animal heart. We present these models as examples to suggest general approaches that physics instructors can use to help biology students develop the practices of modeling.

A. Explanatory models: Cells and atoms

Cells and atoms are canonical structures that serve as quintessential examples of the modeling process and its value in the sciences.[11–16]

It is common in chemistry and in modern physics courses to lead students successively through more sophisticated models of the atom. Often, instructors begin with Thomson's "plum-pudding" model and progress through Rutherford's "planetary" model, Bohr's quantized model, and Schrodinger's "cloud" model. For simplicity, we use only the Rutherford and Bohr models to illustrate the importance of model refinement (see Table I). Rutherford's objective was to explain the scattering of alpha particles in terms of the distribution of charge and mass in an atom. Rutherford's model, though, was unable to explain the emission and absorption spectra of hydrogen, a phenomenon that is well explained by the Bohr model. Bohr's model cannot, however, describe the structure and dynamics of the atom—the later objective of Schrodinger's model. Each model captures different features and behaviors of the atom, and each makes different assumptions about an atom's behavior. In each instance after Thomson's, prior models were tested and refined. Inaccuracies, such as non-discrete electron orbitals, were stripped away as each model was tested against observation and found unable to explain certain phenomena. By focusing on the practice of modeling as an iterative, dynamic process, physics instructors can demonstrate that sound science is not about finding the one "true" model of the atom, but showing that, depending on the available observations and level of detail required, many models may be scientifically useful, despite their limitations. An explicit discussion of scientific models and modeling highlights the features that make a model useful for a given purpose and leads to a discussion of what gives one model greater utility or parsimony than another.

As the atom is the building block of matter, the cell is the building block of life. Cells are frequently modeled in biology curricula, and just as with physical models of the atom, the choices made in the modeling process depend on the objectives. Here, we focus on a model with the purpose of explaining the composition of an idealized cell as the basic unit of life. A key assumption of early cell models (since tested and found valid) is that cells are irreducibly alive; all functions of life, then, occur within cells. Models of idealized cells may be represented by "cartoon" diagrams—highly simplified, roughly scaled drawings, usually with false-colored structures. As with models of the atom, successive models of cells have been tested, validated, and refined, with new features added and extraneous features stripped as new observations invalidated previous assumptions. Some of the first models of the cell were van Leeuwenhoek's seventeenth-century drawings of "animalcules" (microorganisms). Startling in their detail, these were the first representations of cells viewed through a handheld, handmade, first-generation microscope. However, van Leeuwenhoek's model of a sperm cell, in which he thought he observed a tiny homunculus (a fully-formed individual), was subsequently revised as more powerful microscopes afforded more accurate images.

This pair of examples is meant to highlight the essential steps of model validation and refinement. Physics instructors can reinforce this part of the modeling process by choosing and designing problems and cases that build on previous models, so that students develop experience in the sustained and iterative process of model building.

B. Predictive models: Motion of a car and of a bacterial colony

The topics of motion and forces make up a large fraction of introductory physics content. Models of motion are often predictive. These models refer to some particular real-world phenomenon, say, the motion of a car, for which the objective is to predict: a trajectory, velocity, acceleration, or some other kinematic property. Initial versions of these models used in instruction do not account for the mechanisms causing this motion (e.g., using kinematic equations instead of Newton's second law). In predictive models such as models of motion, equations and graphs are common forms of representation. With a foundation of kinematic models, introductory physics courses typically proceed to dynamics, where forces are now enumerated and combined. Gravitational, spring-based, and frictional forces serve as new variables within the model and allow motion prediction across a wide range of circumstances, depending on the particular force.

In biology, the directed motion of groups of cells, termed taxis, is important for cells seeking food or avoiding harm. Chemotaxis allows bacteria to find glucose on a culture plate or avoid antibiotic toxins; it also allows sperm cells to locate oocytes prior to fertilization. Biologists use models to predict the same types of parameters that physicists do: a mean path (akin to center-of-mass motion), a trajectory of motion, and a rate of motion. When modeling chemotaxis, biologists typically assume that the organisms choose an optimal path. Biologist frequently consider populations, or groups of similar-type individuals (whether cells or organisms). Many predictive models in biology are therefore probabilistic, emerging from the collective behavior of many individuals—an important difference between predictive models in physics and biology. As in physics, predictive models in biology are often represented using equations and graphs. Although chemotaxis models provide quantitative predictions of rates and trajectories for a particular chemotactic agent acting on a group of cells, the effect of a new chemotactic agent cannot be predicted.

Physics instructors who wish to emphasize the development of modeling skills can focus on choosing representations that best correspond to the model's purpose, e.g., equations and graphs for predictive models (see Table II). Students do not always see the connection between a model and its representation so the teaching of this correspondence must be explicit. Physics instructors can also choose problems and cases that illuminate the principles of predicting population-level, or probabilistic, outcomes (e.g., the motion of bacterial colonies). Furthermore, since many scientific models have more than one objective, physics instructors can emphasize that such models may employ multiple

representations, such as equations and diagrams. Life science students need frequent practice in negotiating among the representations and model types.

C. Functional models: The Carnot cycle and the heart

Physicists exploring introductory biology textbooks may be surprised at how many of the diagrams portray cycles and processes: life cycles, cell cycles, nutrient cycles, developmental processes, cycles of respiration and photosynthesis. The principles of matter and energy conservation underlie many of these diagrams portraying complicated biological systems. The connection between energy and entropy is critically important for developing systems thinking in introductory biology courses.[4,33]

Heat engines provide familiar examples of cyclic processes in physics, converting thermal energy into mechanical energy as heat flows from one reservoir to another through the engine. A common physical model of a heat engine is the Carnot cycle, which illustrates the principles of energy conservation and entropy changes for a cyclic process in an idealized way: the heat exchanges with the two reservoirs are treated as isothermal processes, while the temperature changes of the working substance are taken to be adiabatic. This cycle is commonly represented graphically, for an ideal gas system, in a *P-V* diagram such as the one shown in Fig. 2(a). The objectives of the model are to describe the functions of the reservoirs and the working substance, and to explain why the efficiency of the engine is limited by the reservoir temperatures. The model omits many real-world complications and does not predict the rate at which the engine performs work.

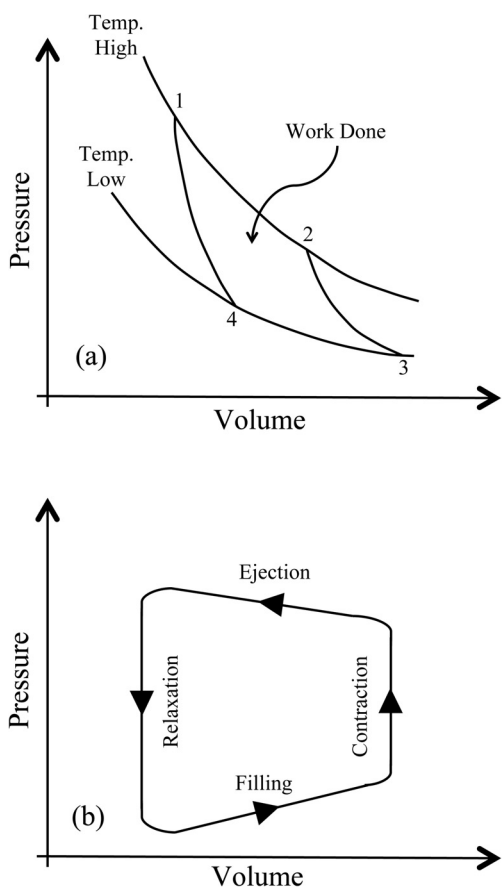


Fig. 2. Functional models often evoke diagrammatic representations, such as these *P-V* diagrams of (a) a Carnot engine and (b) an idealized animal heart.

A biological example of a cyclic mechanism is the animal heart. Animal hearts use energy, supplied from cellular respiration, to do the mechanical work required to move blood throughout the animal's body. Figure 2(b) shows a model of the cyclic operation of the left ventricle of the four-chambered human heart, which sends oxygenated blood into the aorta. At the end-diastolic point (bottom-right of the figure), the left ventricle begins to contract until the pressure inside it exceeds the pressure in the aorta and the blood inside the ventricle is ejected. Blood volume in the ventricle soon decreases and pressure falls, triggering the opening of the mitral valve that initiates ventricular filling. The cycle repeats throughout the organism's lifetime.

This pair of functional models (compared in Table III) demonstrates how models of different systems can be used to convey overarching principles governing how physical and biological systems behave. For example, photosynthesis and respiration can be characterized as thermodynamic processes, as can some homeostatic processes. The Carnot cycle invites physics teachers to emphasize the conservation of matter and energy—a core concept in biology as well as physics.[4] Students have distinct difficulties following matter and energy through biological cycles, believing, for example, that matter and energy can be "used up" or that matter can change into energy.[33] Physics teachers can emphasize this and other models of thermodynamic processes that consider matter and energy as distinct but mutually necessary elements of a real-world system and models of the system.

These models of cyclic processes also illustrate the importance of navigating among the multiple representations of many scientific models. While the Carnot engine and ventricular-function models have clear functional objectives, they are also used to predict how much total work might be done, or the total blood volume able to be moved by a heart. Such predictive features invite mathematical representations. Biology students do not see many mathematical models in their introductory biology courses, so physics teachers can serve students well by emphasizing mathematical representations when they are engaged with predictive models.

V. IMPLICATIONS

In this paper, we have claimed that modeling is a ubiquitous scientific practice, and that a small set of operational elements and principles govern scientific models and modeling in the physical and life sciences. Hence, one powerful way to support interdisciplinary science teaching is to focus instruction on the practice of modeling. Furthermore, these claims suggest possible research questions that explore the design, implementation, and evaluation of model-based instruction.

Science is the practice of modeling, and our examples demonstrate that modeling is fundamentally a shared practice of physics and biology. Models are what we use to make sense of our world; they are tools for understanding natural phenomena. Life science majors would be well served in physics courses where an explicit emphasis is placed on the process of constructing and validating physical models. And yet, most introductory physics courses under-emphasize the concept of a model and the process of modeling. This deficiency is unfortunate, because in their future course work, students will use biological models extensively and engage in the modeling process. Additionally, the modeling process

closely approximates the types of skills that professional biologists will employ throughout their careers. The centrality of modeling as a scientific practice naturally prompts research questions related to the similarities and differences between models and modeling in physical- and life-science instruction. For instance, how does learning modeling differ between physics and life science courses?

While physics and biology appear to have rather distinct disciplinary practices, we argue that an emphasis on modeling can serve to reconcile these two disciplines at their most fundamental level. As a shared practice within the sciences, modeling provides a common framework from which specific disciplinary differences can be compared and elaborated. Differences in the selection of model types result from differences inherent to the systems that each discipline studies, the types of models built (descriptive, predictive, or functional), and common representations (diagrams, graphs, equations, narratives). Unpacking and engaging in the modeling process provides ample opportunities for both instructors and students to describe how and why models in each discipline are developed and used. Specific models from the discipline of biophysics provide an additional means of bridging these two disciplines. Given the emphases on different model types between biology and physics, an important question arises: To what extent are students able to transfer knowledge of the modeling process across biology and physics, and more broadly, among disciplines that emphasize modeling as a practice?

The modeling practice is applicable to every scientific discipline and uses only a small set of core principles. As a result, modeling provides a common language for cross-disciplinary dialogue. Models in biology and physics are defined by one or more objectives—they explain phenomena, they make predictions, and/or they describe functions and processes. All models make simplifying assumptions, employ representations that are aligned with model objectives, and are validated and refined through iterative interaction between experimental observations and model outputs. While specific representations may differ between disciplines, these differences can be understood through their alignment to model objectives. Model representations are essential forms of scientific communication, and an interesting research question relevant across disciplines is: Do certain representations better support students' sense-making about the model or the real world? A closely related question is: How do multiple representations of one model support students' model-building and sense-making skills?

The most common approaches to science curricular reform focus on changes in course content or context. Indeed, a number of teams are working on specific content changes to their introductory courses.[7–10] While these thoughtful approaches are encouraging, it is unlikely that these wholesale course revisions will be adopted broadly, because content-specific changes to the introductory physics courses will ultimately be informed by local conditions. We have provided a complementary view to transforming undergraduate science courses by illustrating how physics and biology are united in their underlying use of scientific models and by describing how this practice can be leveraged to bridge the teaching of physics and biology. Our view complements that of curriculum developers by providing a theoretical scaffold on which to center individual and community efforts. Our work will be further enhanced as curriculum developers and education researchers develop deeper understandings of the mechanisms and impacts of model-based instruction.

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[1]National Science Board, *Science and Engineering Indicators 2012* (National Science Foundation, Arlington, VA, 2012), <http://www.nsf.gov/statistics/seind12/>.
[2]National Research Council, *Discipline-Based Education Research: Understanding and Improving Learning in Undergraduate Science and Engineering* (The National Academies Press, Washington, DC, 2012), <http://www.nap.edu/catalog.php?record_id=13362>.
[3]National Research Council, *Adapting to a Changing World—Challenges and Opportunities in Undergraduate Physics Education* (The National Academies Press, Washington, DC, 2013), <http://www.nap.edu/catalog.php?record_id=18312/>.
[4]*Vision and Change in Undergraduate Biology Education: A Call to Action*, edited by Carol A. Brewer and Diane Smith (AAAS, Washington, DC, 2011), <http://visionandchange.org/finalreport/>.
[5]National Research Council, *Bio2010: Transforming Undergraduate Education for Future Research Biologists* (The National Academies Press, Washington, DC, 2003), <http://www.nap.edu/catalog.php?record_id=10497>.
[6]President's Council of Advisors on Science and Technology, Engage to Excel: Producing One Million Additional College Graduates with Degrees in Science, Technology, Engineering, and Mathematics (Executive Office of the President, Washington, DC, 2012), <http://www.whitehouse.gov/sites/default/files/microsites/ostp/pcast-engage-to-excel-final_2-25-12.pdf/>
[7]D. C. Meredith and E. F. Redish, "Reinventing physics for life-sciences majors," Phys. Today **66**, 38–43 (2013).
[8]J. S. Gouvea, V. Sawtelle, B. D. Geller, and C. Turpen, "A framework for analyzing interdisciplinary tasks: Implications for student learning and curricular design," CBE-Life Sci. Educ. **12**, 187–205 (2013).
[9]B. O'Shea, L. Terry, and W. Benenson, "From $F = ma$ to flying squirrels: Curricular change in an introductory physics course," CBE-Life Sci. Educ. **12**, 230–238 (2013).
[10]K. V. Thompson, J. Chmielewski, M. S. Gaines, C. A. Hrycyna, and W. R. LaCourse, "Competency-based reforms of the undergraduate biology curriculum: Integrating the physical and biological sciences," CBE-Life Sci. Educ. **12**, 162–169 (2013).
[11]K. Cummings, P. W. Laws, E. F. Redish, P. J. Cooney, and E. F. Taylor, *Understanding Physics* (Wiley, Hoboken, NJ, 2004).
[12]D. C. Giancoli, *Physics for Scientists and Engineers with Modern Physics* (Pearson, Upper Saddle River, NJ, 2008).
[13]R. D. Knight, *Physics for Scientists and Engineers: A Strategic Approach* (Pearson/Addison Wesley, Upper Saddle River, NJ, 2004).
[14]R. W. Chabay and B. A. Sherwood, *Matter and Interactions* (Wiley, Hoboken, NJ, 2011).
[15]R. A. Serway, *Physics for Scientists and Engineers* (Cengage Learning, Stamford, CT, 2012).
[16]J. B. Reece, L. A. Urry, M. L. Cain, S. A. Wasserman, P. V. Minorsky, and R. B. Jackson, *Campbell Biology* (Benjamin Cummings, San Francisco, 2010).
[17]R. Brooker, E. Widmaier, L. Graham, and P. Stiling, *Biology* (McGraw-Hill, New York, 2013).
[18]P. Raven, G. Johnson, K. Mason, J. Losos, and S. Singer, *Biology* (McGraw-Hill, New York, 2013).
[19]National Research Council, *A Framework for K-12 Science Education: Practices, Crosscutting Concepts, and Core Ideas* (The National Academies Press, Washington, DC, 2012), <http://www.nap.edu/catalog.php?record_id=13165>.
[20]Achieve, Inc. on behalf of the 26 states and partners that collaborated on the NGSS, *Next Generation Science Standards* (2013), <http://www.nextgenscience.org/next-generation-science-standards>.

[21]M. Wells, D. Hestenes, and G. Swackhamer, "A modeling method for high school physics instruction,", Am. J. Phys. **63**, 606–619 (1995).
[22]E. Etkina and A. Van Heuvelen, "Investigative science learning environment: A science process approach to learning physics," in *Research-Based Reform of University Physics*, edited by E. F. Residh and P. J. Cooney (American Association of Physics Teachers, College Park, MD, 2007), <http://www.per-central.org/document/ServeFile.cfm?ID=4988/>.
[23]A.-M. Hoskinson, "How to build a course in mathematical-biological modeling: Content and processes for knowledge and skill," CBE-Life Sci. Educ. **9**, 333–341 (2010).
[24]D. Hestenes, "Toward a modeling theory of physics instruction," Am. J. Phys. **55**, 440–454 (1987).
[25]I. A. Halloun, *Modeling Theory in Science Education, Vol. 24* (Springer, New York, 2004).
[26]C. V. Schwarz *et al.*, "Developing a learning progression for scientific modeling: Making scientific modeling accessible and meaningful for learners," J. Res. Sci. Teach. **46**, 632–654 (2009).
[27]A. M. Starfield, K. Smith, and A. L. Bleloch, *How to Model It: Problem Solving for the Computer Age* (McGraw-Hill, New York, 1993).
[28]J. Odenbaugh, "Idealized, inaccurate but successful: A pragmatic approach to evaluating models in theoretical ecology," Biol. Philos. **20**, 231–255 (2005).
[29]R. Levins, "The strategy of model building in population biology," Am. Sci. **54**, 421–431 (1966).
[30]J. T. Dauer, J. L. Momsen, E. B. Speth, S. C. Makohon-Moore, and T. M. Long, "Analyzing change in students' gene-to-evolution models in college-level introductory biology," J. Res. Sci. Teach. **50**, 639–659 (2013).
[31]S. McKagan, K. Perkins, and C. Wieman, "Why we should teach the Bohr model and how to teach it effectively," Phys. Rev. Special Top.—Phys. Educ. Res. **4**, 010103-1–10 (2008).
[32]C.-Y. Tsui and D. F. Treagust, "Genetics reasoning with multiple external representations," Res. Sci. Educ. **33**, 111–135 (2003).
[33]J. Rice, J. Doherty, and C. Anderson, "Principles, first and foremost: A tool for understanding biological processes," J. College Sci. Teach. **43**, 74–82 (2014).

Demonstration Condenser

This device can be used for a good modern demonstration. Put the metal plates close to the glass insulator, and charge the device using a nine volt battery. Ground one side, and pull the plates apart without touching them, and a spark may be drawn from the ungrounded plate. How is this possible? Work must be done to pull the plates apart. This apparatus, in the collection of Allegheny College, was made by Ritchie of Boston and cost about $12 in the last quarter of the 19th century. (Notes and photograph by Thomas B. Greenslade, Jr., Kenyon College)