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Assessing students' understanding of computational modeling in physics

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Abstract: Computational modeling is increasingly included in secondary physics curricula. In classroom practice, however, students often work with pre-designed computational models rather than constructing or modifying models themselves. Research on modeling in science education indicates that meaningful engagement with models requires meta-modeling knowledge: an understanding of models' nature, purpose, use, and limitations in scientific inquiry. Yet little is known about how secondary students reason about computational models and how this meta-modeling knowledge can be systematically analyzed. This study adapts the Framework for Modeling Competence (FMC) to the context of physics computational modeling in order to examine students' meta-modeling knowledge. The resulting Framework for Computational Modeling Competence (FCMC) characterizes students' reasoning about computational modeling across five epistemic aspects (*Nature*, *Multiple*, *Purpose*, *Testing*, and *Changing*), each articulated across three levels of understanding. Data were collected through semi-structured interviews with 36 upper secondary pre-university physics students in the Netherlands. Students were asked to reason about two computational physics models, and their utterances were analyzed using the FCMC's aspect–level combinations. The analysis shows that students most frequently demonstrated meta-modeling knowledge related to the *Purpose* and *Testing* aspects of computational models. In contrast, reasoning corresponding to the highest level of understanding was absent for the aspects *Nature*, *Multiple*, and *Changing*. These findings suggest that while students can use computational models to interpret or compare results, they experience greater difficulty reasoning about computational models as epistemic tools involving assumptions, alternative representations, and model revision. The study provides an analytical framework for examining students' meta-modeling knowledge in computational modeling and highlights the need for instructional approaches that explicitly support epistemic reasoning about computational models in physics education.

Keywords: computational modeling, framework assessment, meta-modeling knowledge, student interviews, physics education

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Introduction

In the evolving landscape of physics education, working and learning with computational models is becoming increasingly crucial in secondary education (Fuhrmann et al., 2018; Galili, 2018; Hestenes, 1987; Justi & Gilbert, 2002; Ogborn & Wong, 1984; Van Buuren et al., 2016; Weber & Wilhelm, 2020). Integrating computational modeling elevates physics education by enabling students to explore subjects with greater realism beyond the theoretical scenarios typically found in physics textbooks (Van Buuren et al., 2016). In this study, it is essential to distinguish explicitly between *modeling*, *computational modeling*, and *meta-modeling*. *Modeling* is the scientific practice of constructing, using, testing, and modifying models to represent and investigate physical phenomena (Upmeier zu Belzen et al., 2019). *Computational modeling* is a specific instantiation of this practice in which models are implemented as computational structures—typically sets of difference equations, parameters, and constants—that enable numerical simulation and the exploration of dynamic systems (Humphreys, 2004; Löhner, 2005). *Meta-modeling* concerns students' reflective understanding of models and modeling, particularly their roles, purposes, and uses in scientific inquiry (Schwarz & White, 2005).

Computational models represent dynamic physical phenomena through numerical simulation based on mathematical relations and parameters (Humphreys, 2004; Löhner, 2005). A physics-based computational model comprises a series of mathematical representations, rules, and reasoning structures that enable physicists to describe, investigate, and explain physical phenomena, thereby formulating hypotheses and testing them against reality (Schwarz & White, 2005). An example is the domain of nuclear physics, where scientists simulate radioactive decay using computational models (e.g. García-Toraño et al., 2019). Integrating computational modeling into the physics curriculum enhances students' understanding of fundamental principles, exposes them to scientific methods, enables complex calculations for realistic phenomena, and improves their problem-solving skills (Louca & Zacharia, 2012; Van Buuren, 2014; Weber & Wilhelm, 2020). Given the need for a scientifically literate population, education helps students understand the complexities of scientific processes (Feinstein, 2011; Lederman et al., 2023). Although prior studies show the potential of computational modeling in physics education, existing approaches often treat computational models as add-ons rather than as integrated tools for developing fundamental physics concepts (Aksit & Wiebe, 2020; Barab et al., 2000; Löhner, 2005; Ormel, 2010; Van Borkulo et al., 2012; Van Buuren et al., 2016; Van Buuren, 2014; Weber & Wilhelm, 2020, Banda & Nzabahimana, 2021; Zacharia, 2003, Louca & Zacharia, 2012). Thus, there is a need for research that deliberately connects computational modeling to the learning of fundamental physics concepts, particularly through student-designed computational models expressed as difference equations. The study presented here addresses this need by laying the groundwork for a more integrated approach to learning physics through computational modeling, with a focus on students' meta-modeling knowledge and reasoning about computational models.

In this paper, we use the term *physics education* to refer specifically to secondary school education in the subject of physics. Terms such as *scientific modeling* and *scientific reasoning* refer to general practices within the broader field of science. The adjective *physical* is used to describe phenomena or models that are grounded in physics principles.

Theoretical background

The role of computational modeling and simulations in education has expanded significantly, with studies demonstrating their effectiveness (Grapin et al., 2023; Grosslight et al., 1991; Hestenes, 1987; Louca & Zacharia, 2012; Rachmatullah & Wiebe, 2022; Schwarz et al., 2009; Schwarz & White, 2005; Sins et al., 2009; Weber & Wilhelm, 2020, 2024). However, computational modeling in physics education often focuses more on mastering specific technical computational modeling skills than improving conceptual understanding (Bao & Koenig, 2019; Vieyra et al., 2024). This section reviews research on the educational benefits of computational modeling and examines its current integration into physics education.

Computational modeling in secondary education

Integrating computational modeling into the physics curriculum offers several benefits for students: 1) Learning with computational models enables students to develop a realistic understanding of modeling outcomes and to gain insight into the ways physicists use models in scientific investigations, thereby establishing a clear connection between fundamental physics principles and the formulation of physical theories (Bailer-Jones, 2002; Löhner, 2005; Louca & Zacharia, 2012; Schwarz et al., 2009; Schwarz & White, 2005; Weber & Wilhelm, 2020). 2) Computational models enable students to perform more complex calculations than they can do manually, allowing them to investigate more realistic physical phenomena (Löhner, 2005). 3) Utilizing computational models for physics education allows students to learn to solve physics-oriented problems (Phillips et al., 2023).

Despite the growing importance of computational modeling in education, recent studies indicate that it is not always well-integrated into the physics curriculum (Ormel, 2010; Van Buuren et al., 2016; Weber & Wilhelm, 2020). Often, the focus is on learning how to use a particular computational modeling environment rather than on learning subject-specific and curriculum-related physics concepts (Schwarz & White, 2005; Seoane et al., 2022; Weber & Wilhelm, 2020). Additionally, the focus tends to be on conducting physics experiments, in which students formulate a mathematical connection to a particular physics process (Angell et al., 2008; Van Buuren, 2014). As a result, students frequently work primarily with pre-designed computational models instead of designing their own to investigate and describe physical concepts. This limits the full potential of computational modeling in education, as it does not fully leverage the benefits of allowing students to actively engage in developing and refining computational models, which is crucial for a deeper understanding of physics and the nature of scientific inquiry (Schwarz & White, 2005).

Framework for assessing meta-modeling knowledge in computational modeling

Engaging in the creation of computational models aids students in recognizing that scientific knowledge is a human creation (Wild, 1996), that computational models exhibit variability in their capacity to approximate and predict physical phenomena (Gilbert, 1991), and fosters an understanding of scientific inquiry and scientific practices, increasing *"(...) knowledge about the nature and purpose of scientific models"* (Schwarz & White, 2005, p. 166). This type of knowledge is characterized as "meta-modeling knowledge": the knowledge that students "…*need to understand how models are used, why they are used, and what their strengths and limitations are, in order to appreciate how science works and the dynamic nature of knowledge that science produces*" (Schwarz et al., 2009, p. 634-635). To materialize this concept of meta-modeling knowledge (Göhner et al., 2022; Schwarz & White, 2005) and determine in what ways computational models contribute to the development of students' meta-modeling knowledge, we need a theoretical framework appropriate for assessing students' meta-modeling knowledge in the context of computational modeling (Gogolin & Krüger, 2018; Grosslight et al., 1991; Schwarz & White, 2005; Treagust et al., 2002).

The Framework for Modeling Competence (FMC) (Göhner et al., 2022; Upmeier zu Belzen et al., 2019) provides a structure for assessing meta-modeling knowledge as a part of natural science understanding, involving the use of scientific models as research tools and scientific modeling as a research practice (Table 1). The FMC uses five aspects that reflect scientific modeling understanding: *Nature of models*, *Multiple models*, *Purpose of models*, *Testing models,* and *Changing models*, hereinafter referred to as *Nature*, *Multiple*, *Purpose*, *Testing,* and *Changing*.

Table 1

Framework for Modeling Competence (FMC) with five aspects and three levels of understanding (Upmeier zu Belzen et al., 2019; Göhner et al., 2022)

Aspects	Level I	Level II	Level III
Nature of Models	Replication of the phenomenon	Idealized representation of the phenomenon	Theoretical reconstruction of the phenomenon
Multiple Models	Different model objects	Different foci on the phenomenon	Different hypotheses about the phenomenon
Purpose of Models	Describing the phenomenon	Explaining the phenomenon	Predicting something about the phenomenon
Testing Models	Testing the model object	Comparing the model and the phenomenon	Testing hypotheses about the phenomenon
Changing Models	Correcting defects in the model object	Revising due to new insights	Revising due to the falsification of hypotheses about the phenomenon

These aspects describe epistemic characteristics of models and modeling that students may understand to varying degrees. The aspect *Nature* concerns students' understanding of what models are, ranging from viewing models as direct replicas of reality to understanding them as idealized or theoretical reconstructions of phenomena. The aspect *Multiple* addresses students' understanding that multiple models can exist for the same phenomenon, reflecting different assumptions, purposes, or theoretical perspectives. The *Purpose* aspect focuses on why models are used, distinguishing between descriptive and explanatory uses, and between using models as tools for generating predictions and for developing new knowledge. The aspect *Testing* concerns how models are evaluated, ranging from superficial checks of model appearance or functionality to systematic testing of hypotheses derived from models. Finally, the *Changing* aspect addresses students' understanding of why and how models are revised, from correcting apparent flaws to revising models in response to new evidence or falsified hypotheses. Together, these aspects describe key epistemic characteristics of models and modeling that are central to understanding models as tools for scientific inquiry rather than merely as representations of known phenomena. Each aspect is elaborated across three levels of understanding (Level I, Level II, and Level III), representing an epistemic progression from descriptive, product-oriented views of models to more advanced, epistemically informed views of models as tools for scientific inquiry (Göhner et al., 2022; Upmeier zu Belzen et al., 2019). Importantly, these levels do not represent a linear learning progression nor mutually exclusive stages of development. Rather, they describe epistemic orientations that may co-occur within students' reasoning and across different aspects, depending on context and task. Empirical studies have shown that combining aspects and levels is necessary to systematically analyze qualitative differences in students' understanding of scientific models (Grünkorn et al., 2014; Jansen et al., 2019).

These analytic categories serve to make visible different manifestations of modeling competence across aspects and levels; therefore, they are used as analytic lenses rather than as discrete, independently assessable competencies. The FMC was originally developed to describe modeling competence within the natural sciences more broadly. In this article, we explicitly address meta-modeling knowledge in the specific context of physics computational modeling. Building on the FMC, the present study adapts its epistemic structure to the domain of computational models in physics. The five FMC aspects are retained as substantive dimensions of meta-modeling knowledge and applied to students' reasoning about computational models.

To account for the specific epistemic features of computational models in physics, the further specification of these analytic categories for computational modeling is informed by existing literature on computational modeling, numerical methods, and model-based reasoning in physics education. This literature is discussed in the following paragraph and provides the theoretical grounding for developing a domain-specific framework to analyze students' meta-modeling knowledge in computational modeling.

Airey's (2019) interview study analyzes students' understanding of physical equations by identifying distinct ways in which equations are interpreted and used in physics reasoning. This is particularly relevant for computational modeling, as such models typically consist of physics-based difference equations closely related to analytical physical equations (Fulford et al., 1997; Humphreys, 2004). When computational models aim to describe realistic physical situations, the governing equations often arise from second-order nonlinear differential equations, which must be solved numerically by reformulating them as difference equations (Humphreys, 2004). From a philosophical perspective, Redhead (1980) examines how formulas function as theoretical models in physics, emphasizing their role in representing, idealizing, and interpreting physical phenomena. In this view, physical formulas do not merely serve as calculational tools, but constitute structured theoretical representations that underpin explanation and prediction. Such an epistemic understanding of formulas as models provides an important foundation for translating analytical models into difference equations for use in computational modeling (Taha et al., 2021). Several studies in science education have examined students' understanding of scientific models and modeling from a meta-level perspective. Oh and Oh (2011) identify recurring themes in how models are conceptualized and used in science education, including the purpose and meaning of models, the coexistence of multiple models, and the development and change of models over time. Schwarz and White (2005) similarly investigate students' metamodeling knowledge through interviews and analyses of instructional materials, focusing on students' understanding of the nature, purpose, and evaluation of scientific models, as well as the modeling process itself. Other strands of the literature conceptualize modeling explicitly in terms of competence. Constantinou et al. (2019), for example, present a modeling-based learning framework in which modeling is treated as a competence that can be developed, supported, and assessed in educational contexts. Within a related competence-oriented tradition, Grünkorn et al. (2014) evaluate and refine a framework for assessing students' modeling competence, conceptualizing it as comprising several components related to epistemic practices in modeling. While these competence components are not adopted as analytic units in the present study, their focus on epistemic demands—such as testing hypotheses through research designs and reasoning about abstract ideas—resonates with the analytic categories used here. In contrast to competence-oriented approaches found in parts of the literature (e.g., Constantinou et al., 2019), the present study adopts an analytic perspective, examining students' reasoning about computational models through aspect–level categories informed by this body of literature. The literature discussed above informs the domain-specific content of the framework developed in this study, while the epistemic structure of the FMC (Upmeier zu Belzen et al., 2019) was adapted to the context of computational modeling to assess students' meta-modeling knowledge. In addition to providing the overarching aspect–level structure, the FMC also offers an epistemic characterization of modeling practices, such as hypothesis generation, experimentation, and model revision, which is retained and specified for the context of computational modeling. The final result of the adjustment process is the *Framework for Computational Modeling Competence*, hereafter referred to as "FCMC". Within the FCMC, the five FMC aspects serve as the core analytical structure and are elaborated across three levels of understanding to capture qualitative differences in students' reasoning about computational models in physics. For each aspect, the three levels describe distinct ways in which that aspect may be understood, yielding a total of fifteen aspect–level combinations. These combinations serve as analytic categories to examine qualitative differences in how students reason about computational models across increasing levels of epistemic sophistication.

Across all five aspects, these levels are defined as follows:

> Level I: The ability to judge the appearance of the computational model as a representation of reality.
>
> Level II: The ability to assess the process of the computational model: the understanding that parameters are present and that these parameters can affect the modeling process, thereby the model acts as a more or less accurate representation of a natural scientific phenomenon, and that the model is representative of something already known in the natural sciences.
>
> Level III: The ability to use a computational model for scientific activities to investigate a scientific phenomenon and thereby assess its productivity; the model object as a model for something leads to the processing of new, hitherto unexplained scientific questions.

According to the research by Passmore et al. (2014) and Krell et al. (2013), the three levels reflect a qualitative difference in epistemic orientation. Level I is characterized by a descriptive approach, in which computational models are primarily viewed as visual or numerical representations of phenomena. Level II reflects an explanatory approach, in which computational models are understood as tools for analyzing relationships, mechanisms, and parameter influence. Level III represents a prospective approach, in which computational models are used to formulate hypotheses, generate predictions, and systematically test them to produce new scientific insights. Table 2 presents the FCMC and the literature informing its development. This table specifies, for each FMC aspect and each level of understanding, theoretically grounded descriptions of characteristic ways in which students may reason about computational models and computational modeling. Together, these aspect–level descriptions form a proposed analytical framework for examining and interpreting student utterances in the present study.

In this research, the FCMC is used to explore how students' meta-modeling knowledge in computational modeling can be characterized through their verbal reasoning. By analyzing how students' utterances align with the proposed aspect–level categories, the study provides an analytical basis for examining students' meta-modeling knowledge and reflecting on the framework's applicability. Concrete examples of how such reasoning is expressed in student utterances are illustrated in the Results section using empirical data. In line with the FMC (Upmeier zu Belzen et al., 2019; Göhner et al., 2022), modeling competence is treated here as a holistic construct. The combinations of aspects and levels used in the FCMC serve as analytic categories, making visible different manifestations of students' meta-modeling knowledge.

Theoretical rationale for interpreting student utterances as indicators of modeling competence

In this study, student utterances are interpreted as manifestations of students' underlying meta-modeling knowledge in computational modeling. This interpretation is grounded in theories of competency assessment, meta-modeling knowledge, and computational literacy. Previous work by Grünkorn et al. (2014) demonstrates that open-ended student responses can serve as valid indicators of meta-modeling knowledge, provided they are systematically analyzed within a theoretically grounded framework centered on epistemic aspects. Their empirically informed framework shows that qualitative differences in students' understanding of scientific models can be meaningfully identified when student utterances are interpreted in relation to such aspects and levels of understanding. Building on this line of work, the present study adopts the epistemic perspective on modeling competence articulated in the Framework for Modeling Competence (FMC) (Upmeier zu Belzen et al., 2019), in which modeling is understood as a scientific practice closely connected to other investigative practices such as observation and reasoning.

Student utterances about computational models can thus be interpreted as expressions of students' meta-modeling knowledge, provided they are situated within a meaningful task or problem context. This approach aligns with the grand structural model of competence proposed by Blömeke et al. (2015), which conceptualizes competence as a continuum ranging from latent cognitive and motivational dispositions to observable behavior. Within this model, students' verbal utterances and reflections constitute observable indicators that, when analyzed in relation to the task and domain, can be used to infer underlying modeling competence. In addition, Weller et al. (2021) argue that verbal interactions in computational contexts can serve as evidence of students' computational thinking, further supporting the interpretation of student utterances as meaningful indicators of underlying reasoning rather than as isolated task-related responses.

Table 2
Overview of the Framework for Computational Modeling Competence (FCMC).

Aspect of physics computational modeling	Level I		Level II		Level III	
	Characteristic reasoning about physics computational modeling	**Based on (Reference(s))**	**Characteristic reasoning about physics computational modeling**	**Based on (Reference(s))**	**Characteristic reasoning about physics computational modeling**	**Based on (Reference(s))**
Nature	A set of equations describing reality in a computational model	(Airey et al., 2019)	Computational model with parameters and constants based on assumptions	(Redhead, 1980)	Computational model as a resource for theorizing, based on principles and concepts	(Upmeier zu Belzen et al. (2019))
Multiple	Different computational model properties of the same phenomenon	(Upmeier zu Belzen et al. (2019))	Computational model focusing on different aspects of the same phenomenon	(Upmeier zu Belzen et al. (2019))	Different hypotheses about the phenomenon expressed through computational models	(Upmeier zu Belzen et al. (2019) ; Oh & Oh, 2011)
Purpose	Showing the facts with a computational model	(Upmeier zu Belzen et al. (2019))	Identifying and explaining relationships using a computational model	(Constantinou et al., 2019; Grünkorn et al., 2014)	Examining concrete and abstract ideas using computational models	(Upmeier zu Belzen et al. (2019))
Testing	Testing of basic requirements of a computational model	(Upmeier zu Belzen et al. (2019))	Investigating characteristics of the computational model	(Schwarz & White, 2005)	Testing hypotheses with research designs using computational models	(Upmeier zu Belzen et al. (2019))
Changing	Alterations to improve the computational model	(Upmeier zu Belzen et al. (2019))	Alterations due to new findings of the original computational model	(Upmeier zu Belzen et al. (2019))	Alterations due to findings from computational model experiments	(Upmeier zu Belzen et al. (2019))

Further theoretical support is provided by the knowledge-in-pieces perspective articulated by diSessa (2018), which can be understood as the progressive organization of initially fragmented knowledge into more coherent structures. Applied to computational modeling, this perspective suggests that students' utterances can reveal how physical and computational ideas are integrated over time. Empirical studies by Odden et al. (2019) and Odden and Zwickl (2025) illustrate how students' model-related utterances, when carefully contextualized, can provide insight into their epistemological understanding of models and modeling practices. Together, these theoretical and empirical perspectives support the use of student utterances in this study as valid and meaningful indicators of students' meta-modeling knowledge in computational modeling, when analyzed within a coherent analytic framework.

Research Questions of the Study

This study aims to achieve two objectives: to determine whether students' computational modeling competence, as manifested through aspect-level reasoning, can be identified using the FCMC, and to utilize this framework to assess students' level of meta-modeling knowledge in computational modeling. We therefore formulate two research questions:

RQ1: What is the applicability of the Framework for Computational Modeling Competence for analyzing pre-university students' meta-modeling knowledge in computational modeling in physics education?

RQ2: What levels of understanding do upper-level pre-university students demonstrate across different aspects of meta-modeling knowledge in computational modeling?

To answer the research questions, an interview study was conducted. We provided students with computational models to address meta-modeling-based questions about those models and asked them to review the material. Based on students' utterances, we analyzed whether elements of the FCMC could be identified in their reasoning by coding responses according to the framework's aspect–level combinations. This also allowed us to provide an overview of the population's level of understanding of computational meta-modeling knowledge.

Method

Situation and context

This study was conducted in the Netherlands with thirty-six upper secondary students (aged 16–18) enrolled in pre-university education (grade 12), the highest level of secondary education in the Dutch school system. The schools were chosen to be distributed nationwide, covering seven of the twelve provinces. Computational modeling is a mandatory component of the national physics curriculum at this level (Kooij et al., 2023). However, no national regulations stipulate when and in what form this topic should be addressed. As a result, the exact timing and emphasis of this topic can vary between schools, teachers, and textbooks. Some introduce it as early as grade 10, others in grade 12, and some revisit it throughout the upper grades when relevant to specific physics topics. As a result, not all participating students had the same prior experience with computational models.

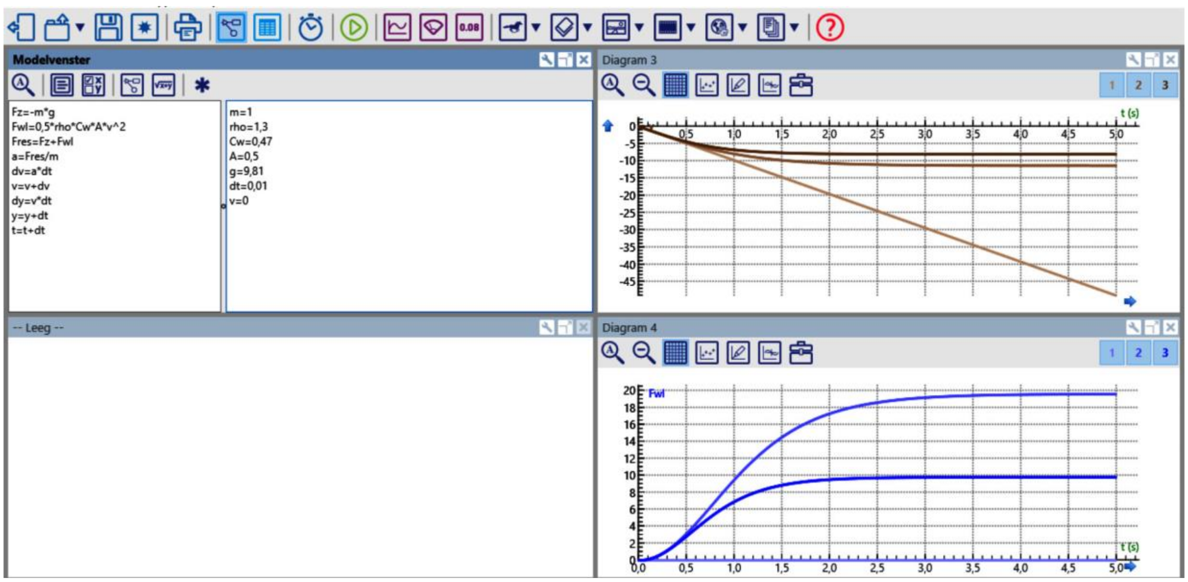
The interviewed students were selected by their physics teacher and were interviewed individually. Students were selected to represent a cross-section of their class groups, encompassing higher-, average-, and lower-performing students, as well as a diverse gender representation (16 female and 20 male students). Although the selection was stratified in this manner, no additional filtering was applied based on prior exposure to computational modeling or interest in physics. All interviews were conducted individually and in Dutch, allowing students to express their ideas in their native language. The answers given were recorded with an audio recorder. The interviews followed a semi-structured format, consisting of predefined questions about two computational models, complemented by follow-up questions to probe students' reasoning in more depth (Maxwell, 2012). On average, interviews lasted approximately 45 minutes. Students received a €15 gift voucher for their participation. These contextual factors—particularly the curricular status of computational modeling, the variability in student experience, and the sampling approach—should be considered when interpreting the findings and evaluating their relevance to other educational settings.

Instruments

During the interviews, we presented two computational physics models: a falling-object model (Figure 1) and a radioactive decay model (Figure 2). All students had been taught these subjects earlier in their school career, and none had any prior preparation regarding the interview content. Both computational models consisted of a set of equations (difference and algebraic equations). The models were implemented using the digital learning environment Coach (Heck et al., 2009). Coach is a versatile software platform that allows students to work with computational models, conduct video measurements, and produce measurement data. This software environment is used in many Dutch secondary schools and was familiar to most of the students interviewed.
An oral explanation of the content of both computational models was given to the students at the start of the interview. During the interviews, students were shown the computer models in Figures 1 and 2. Questions related to these computer models were then asked. All the questions relate to an aspect of the FCMC. For example, the question "What would be a scientist's purpose in creating such a computer model?" relates to the *Purpose* aspect and is intended to encourage students to consider the purpose(s) for which the computer model could be used. A question like "What would be a reason for a scientist to change something about the model?" is related to the *Changing* aspect and is designed to gain insight into students' thinking about how a physics computational model might be used in scientific research. Pilot interviews were conducted with three students (in addition to the participants) prior to the interviews in this study to refine the interview questions. See Supplementary Material A for the interview scheme and an overview of the intended aspect to which the questions belong.

Figure 1

Computational model of a falling object. On the upper left are the difference equations; next to them are the initial values. In the upper right is a velocity-time diagram showing three graphs, each based on a particular condition (e.g., frontal area or friction). In the lower right is a friction force-time diagram containing three graphs, each corresponding to one in the upper right.



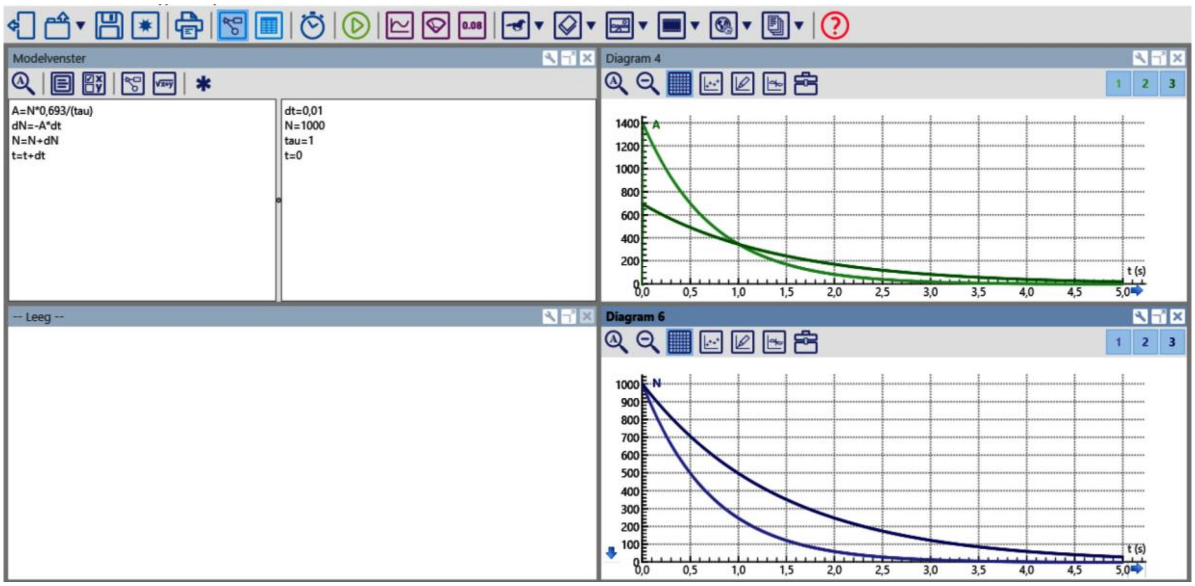
Data collection and analysis

After transcribing the interviews, student utterances were classified by aspect and level in the FCMC. This coding process resulted in 699 coded response elements, categorized into the five aspects and three levels of the FCMC. This classification was conducted by examining relevant student utterances and associating them with a specific aspect and the corresponding level of understanding of the FCMC. By examining how a student's statement aligns with a specific FCMC aspect and level of understanding, and by articulating the underlying rationale, each utterance is assigned to an appropriate analytic category representing meta-modeling knowledge, provided that the utterance meets the coding criteria. Supplementary Material B provides an overview, prepared before the interviews, of the requirements a student's utterance must meet to be coded into a particular category in the FCMC.

An independent second coder coded 24 randomly selected students' response elements, of which 22 matched the first coding regarding the model aspect. This second coding served as qualitative verification of the coding scheme's interpretive consistency rather than as a formal assessment of interrater reliability. Within these model aspects, the initial levels of understanding coded by the second coder differ from those of the first coder for *Purpose*, Levels II and III, and *Testing*, Levels II and III. After discussing the differences in aspects and levels, an agreement was reached. A follow-up check of the response items for both aspects did not result in significant adjustments.

Figure 2

Computational model of radioactive decay. On the upper left are the difference equations; next to them are the initial values. In the upper right, an activity-time diagram shows two graphs, each based on a specific condition (in this case, a different half-life). A nuclei-time diagram on the lower right includes two graphs, each corresponding to the graphs in the upper right.



Examples of utterances that qualified for coding within the FCMC

We provide illustrative examples of students' utterances suitable for coding. These examples clarify the characteristics that led an utterance to be interpreted as an expression of meta-modeling knowledge and, therefore, to be assigned to a specific aspect–level category within the FCMC. The examples are drawn from both computational contexts used in the interviews (free fall and radioactive decay) to illustrate the domain-independent application of the FCMC.

The larger the half-life, the longer it takes for half the number of nuclei to decay.

This utterance is coded as *Nature*, Level I because the student treats the computational model as a direct representation of the phenomenon by identifying a relation between two quantities in the model's output. The statement focuses on reading and interpreting model results without reference to the model's underlying assumptions, idealizations, or theoretical nature. This reflects a descriptive understanding of models, characteristic of Level I within the *Nature* aspect.

You wouldn't be able to work out the correlation properly on paper, so you could look at a correlation between the maximum velocity and the mass, because now you get the plateau you're going to get at some point, then you can go and make a plot of that to see what the correlation is.

This utterance is coded as *Purpose, Level II* because the student uses the computational model to investigate and analyze relationships between quantities. The model serves here as an analytical tool to reveal connections that cannot be easily deduced. This reflects an explanatory use of models, consistent with Level II of the *Purpose* aspect.

If you want to determine the age of something, you can create a new particle by colliding two particles together. By measuring the activity of the new particle, you can establish how much activity should be present and use this data to plot a graph based on multiple particles.

This statement is coded as *Testing*, Level III because the student uses the computational model as a research tool to test hypotheses about radioactive decay. By linking model outcomes to measured activity and comparing them across multiple systems, the model is used to investigate its validity and applicability. This is consistent with Level III of the *Testing* aspect, in which models are used within research designs to test hypotheses.

Examples of utterances that did not qualify for coding within the FCMC

In addition to utterances that did qualify for coding in the FCMC, several students' utterances lacked the necessary meta-modeling knowledge and therefore did not qualify for coding. For instance, some students mentioned the speed at which a computer performs calculations as the purpose of working with a computational model. However, this does not demonstrate an understanding of meta-modeling, as it fails to acknowledge the scientific modeling process and how this understanding is applied to develop and reason with computational models. Instead, it cites only one advantage of working with a computer.

Some students name the relationship between the size of a time step and the accuracy of a model outcome:

If you take 0.4 s as the time step, the answer differs from that obtained with a time step of 0.01 s. So then it looks a bit less accurate, and it [the graph] also looks a bit more blocky.

This utterance does not demonstrate meta-modeling knowledge because it lacks an understanding of the purpose of computational modeling: to investigate scientific phenomena and create scientific knowledge. This type of answer says something about the (in this case: reduced) accuracy with which model outcomes are represented. Additionally, the impact of changing a time step on the accuracy of the modeling process depends on the numerical approximation method used by the digital learning environment.

Another common rationale for employing computational models is to enhance the delivery of physics lessons by offering explanatory support. In such instances, the computational model serves as a supportive tool rather than being used to test the conceptualization, objectives, and assessment of scientific models. Answers of this type do not contain meta-modeling knowledge and are therefore not coded as such.

The following example is a student’s answer to the question about the purpose of the computational model of the motion of a falling body:

The first thing that comes to mind is using computer models for game development. […]. In that respect, the physics model remains, not for research purposes, but for entertainment.

This student names the use of computational models for developing computer games. This answer does not demonstrate meta-modeling knowledge (which this student implicitly confirms) because it lacks elements that reflect the scientific purpose of computational modeling, such as identifying and explaining relationships.

Students' responses of this type, i.e., responses showing no understanding of meta-modeling knowledge, were not coded.

Results

After coding all 699 response elements from the falling-object and radioactive-decay models, twelve of the fifteen analytic categories of the Framework for Computational Modeling Competence (FCMC) were populated with at least one student utterance. For each aspect, students were assigned to the highest level of understanding for which at least one utterance was coded. An overview of the distribution of students across aspects and levels of understanding is presented in Table 3, based on the highest level each student attained within each aspect.

Table 3

Distribution of students across levels of understanding per aspect. For each aspect, students are counted once at the highest level for which at least one utterance was coded.

Aspect	Level I	Level II	Level III
Nature of computational models	3	33	0
Multiple computational models	3	33	0
Purpose of computational models	3	15	18
Testing computational models	7	20	8
Changing computational models	19	17	0

** Totals per aspect may be lower than 36 because not every student produced codable utterances for each aspect. For Testing, one student produced no codable utterances; therefore, the total is 35.*

To illustrate how student utterances were analyzed using the FCMC, selected interview data are discussed below. These utterances are representative of broader patterns in the dataset and serve to make the framework's analytical application explicit. The utterances are organized by FCMC aspect and illustrate how different levels of understanding manifest within each aspect. For each excerpt, the assigned aspect and level of understanding are explained. Additional illustrative student utterances that were used during the analysis are provided in Supplementary Material C.

Nature of computational models

Utterances coded as *Nature*, Level I, are characterized by a descriptive approach to the model as a representation. For example, a student stated: *You can infer several details directly, such as the time and your velocity at that moment. You can also determine the nature of the movement by examining the graph.* This utterance is coded as *Nature*, Level I, because the model is understood here as a graphical representation from which properties of the movement can be read directly, without reflection on assumptions or limitations of the model. At *Nature*, Level II, students explicitly recognise that computational models are simplifications of reality. One student remarked: *I think if you can adjust it perfectly for all the variables that nature has, then you can make quite a realistic model. Suppose you include variables such as wind direction in the model, you could get quite close.* This utterance is coded as *Nature*, Level II, because the student states that the model's accuracy depends on the variables included, thereby recognizing the model's idealized nature.

Multiple computational models

Within the *Multiple* aspect, Level I utterances primarily concern the use of multiple representations. One student stated: *It's impossible to include all these variables in a single diagram, so you need separate diagrams.* This utterance is coded as *Multiple*, Level I, because the student discusses different diagrams to represent quantities without referring to distinct models or perspectives on the phenomenon. At Level II, it is recognized that different models can lead to different outcomes. One student stated: *Using multiple models for the same situation provides various perspectives, allowing you to average the predictions, which could potentially be more accurate than relying on a single model.* This utterance is coded as *Multiple*, Level II, because the student explicitly states that multiple models can produce different predictions that need to be compared.

Purpose of computational models

For the *Purpose* aspect, Level II utterances indicate that models are used as research tools. For example, when asked about the purpose of a scientist developing such a model, one student replied *To gather specific data on a radioactive substance. This can be readily used to measure radioactivity at different times, which is not possible in real life.* This utterance is coded as *Purpose*, Level II, because the model is used to investigate relationships and data that are difficult to access experimentally. Utterances at *Purpose*, Level III, emphasize the prospective use of computational models. One student stated: *To predict the outcome of an experiment, particularly if it cannot be carried out physically, you might create a model, such as for planetary orbits. By experimenting with the model, you can understand why something works. This enables you to predict or simulate experiments that are not feasible to perform in reality.* This utterance is coded as *Purpose*, Level III, because the model is understood here as a tool for simulating hypothetical experiments and generating new insights.

Testing computational models

At *Testing*, Level II, students describe testing models by comparing them with measurements. One student stated: *In practice, you have a device called a Geiger-Müller counter, and you can see how many seconds it takes for half of the particles to react, what the counter reads, and then, when it is half, convert the time to the number of seconds and compare it with the computer model.* This utterance is coded as *Testing*, Level II, because testing occurs within the model's original context and because the student explicitly proposes comparing model outcomes with empirical measurements to evaluate whether the model aligns with observed data. At *Testing*, Level III, the model is used to systematically vary conditions. For example, one student stated: *You could drop a square instead of a cube, which would have a different air-drag coefficient and create a different diagram. You could also change the size of the object or conduct the experiment on a different planet.* This utterance is coded as *Testing*, Level III, because the student explicitly proposes changing parameters and contexts to investigate the model's applicability.

Changing computational models

Utterances at *Changing*, Level I focus on corrective adjustments. One student remarked: *To make the model as close to reality as possible, you should adjust the initial values.* This utterance is coded as *Changing*, Level I, because adjusting the model is seen here as a way to improve accuracy, without reference to new insights or reinterpretation. In *Changing*, Level II, students describe model changes in response to new information or inconsistencies. One student stated: *If a measurement is incorrect, the researcher must adjust the data. If the graph shows constant velocity but the observations indicate acceleration, the data must be updated to reflect this, thereby altering the graph.* This utterance is coded as *Changing*, Level II, because the student recognizes that models need to be adjusted when observations do not match predictions.

Synthesis across aspects

Together, these examples show how student utterances were analyzed by positioning them within specific aspects and levels of the FCMC. Although Level III utterances occur in the aspects *Purpose* and *Testing*, they are absent in *Nature*, *Multiple*, and *Changing*, indicating an uneven distribution of higher-level epistemic reasoning across the different aspects of computational modeling. Table 3 further substantiates this pattern by showing that students' highest achieved levels differ markedly across aspects.

Notable insights from student utterances

Below are some utterances from student responses during the interviews that stand out for their meta-modeling knowledge. These utterances stand out because they contain relatively more meta-modeling-related content than other students' general answers. The answers are not directly related to the subject content of the computer models shown to the students during the interviews.

In response to the question, 'Why is there not just one model for that theme, but several models for the same theme?' a student gave the following answer:

Suppose you want to investigate something theoretically to see if it is so, but it does not follow the usual laws, for example, something with quantum mechanics. After all, it follows different rules from classical laws, and such a process cannot be simulated with a standard program but requires a different kind of software. [This utterance has been coded as *Multiple*, Level I.]

This answer is notable because it highlights a key concept in computational physics: the need for different models or simulation software depending on the underlying physics. The student recognizes that certain phenomena, such as those in quantum mechanics, follow fundamentally different rules from those in classical physics and cannot be simulated using the same models or software. This shows an understanding that different physical regimes require specialized modeling approaches because they rely on different mathematical frameworks, such as Newtonian and quantum mechanics.

Additionally, another student emphasizes that standard tools may be inadequate for certain phenomena, highlighting the adaptability required in scientific modeling in response to the question, ‘Could the model be used for another purpose?’:

Suppose you fall out of the ISS and start orbiting the Earth; how long will it take you to get back? And do you then orbit Earth more times than the space station, or does the station orbit you more often? The results are surprising: although you go faster and have a higher velocity, you make fewer orbits than the space station. [This utterance has been coded as *Purpose*, Level III.]

This student's answer is notable because it demonstrates an understanding of the purpose of using a computer model to explore complex scenarios that are difficult to grasp intuitively. The scenario described—falling out of the ISS and orbiting Earth—represents a situation where multiple physical factors, such as relative velocities, orbital mechanics, and gravitational forces, interact in ways that are not immediately obvious. By referencing surprising results (i.e., that despite a higher velocity, the falling object completes fewer orbits), the student shows an appreciation for how computer models can reveal counterintuitive outcomes, providing insights that might not be apparent through simple reasoning. This reflects a deeper understanding of how computational models are used to predict, explore, and understand complex physical dynamics.

The following student's answer to the question ‘How is it determined whether the model is correct?’ is notable for highlighting a crucial balance in scientific modeling: the trade-off between accuracy and practicality.

Suppose you want to create a completely accurate model of something down to the level of atoms. You would then need to represent hundreds of billions of particles, which would probably require a computer larger than an entire building, even with current technology. Moreover, developing such a model would take much more time than simply building and testing a physical prototype. The key is to know when to stop *modeling, so it is easier to test in practice than to keep modeling.* [This utterance has been coded as *Purpose*, Level II.]

This student recognizes that while it's theoretically possible to create a highly detailed and accurate computational model, down to the level of individual atoms, such an endeavor can become computationally overwhelming and impractical with current technology. The student points out that there is a point where continuing to refine a model becomes less efficient than simply testing a physical prototype, demonstrating an understanding of the limitations of computational modeling. This insight reflects a sophisticated grasp of the purpose of scientific models in physics: they are tools for approximating reality, but there is always a trade-off between the level of detail and the resources (time, computational power) required to achieve that detail.

No clear model-specific patterns were observed in this study: student utterances qualifying for coding were distributed across both computational models (falling object and radioactive decay), and similar types of reasoning were identified for each model.

Discussion

Applicability of the FCMC

Regarding the first research question in this study, we investigated whether students' meta-modeling knowledge in computational modeling could be assessed based on their utterances in an interview using two physics computational models, using an adjusted version of the FMC (Göhner et al., 2022; Upmeier zu Belzen et al., 2019) for computational models: the Framework for Computational Modeling Competence (FCMC). We also investigated the extent to which the interviewed students demonstrated meta-modeling knowledge.

To assess students' meta-modeling knowledge in computational modeling, we developed the Framework for Computational Modeling Competence by adapting the epistemic aspects and levels of the Framework for Modeling Competence and drawing on related frameworks and the literature on meta-modeling knowledge. This adaptation has enabled us to interpret students' utterances through computational modeling. The interviews help make concrete manifestations of modeling competence, revealing what students think and say about computational models. Our results show that we could identify utterances for all but three cells in the FCMC. This highlights the framework's utility in capturing a broad spectrum of meta-modeling knowledge across diverse forms of reasoning in computational modeling. By providing a structured approach to evaluating students' reasoning, the FCMC enables the identification of the levels of understanding reflected in students' utterances across different aspects of computational modeling, while also making visible those areas of the framework that warrant further elaboration, thereby contributing to a deeper understanding of computational modeling in secondary education and related educational contexts.

Identification of the meta-modeling knowledge of the students interviewed

The second research question in this study explores students' meta-modeling knowledge in computational modeling. After analyzing all student responses, nearly all students scored within twelve of the fifteen aspect–level categories of the FCMC. Although students reasoned about two different computational models, the analytical focus of this study was on students' meta-modeling knowledge, which concerns epistemic reasoning about models and modeling practices rather than topic-specific physics content. Consequently, the study was not designed to compare models quantitatively across different physical domains.

The aspects *Purpose* and *Testing* show scores at all three levels of understanding. For *Purpose*, there is a relatively even distribution across Level II and Level III, with slightly more students reaching Level III. This suggests well-developed meta-modeling knowledge regarding the purpose for which computational models can be used. In contrast, most students achieved Level II as their highest score on *Testing*, while the number of students attaining Level III is slightly higher than those at Level I. This suggests that while students demonstrate some ability to engage with *Testing* at advanced levels, some gaps remain compared to Level II understanding. This may be because, although conducting research through computational modeling is a mandatory part of the upper-level pre-university physics curriculum in the Netherlands, not all the students interviewed had been taught this level of meta-modeling knowledge.

The aspects *Nature*, *Multiple*, and *Changing* do not have scores for Level III understanding. To be assessed at Level III within the *Nature* aspect, students must understand that a computational model is more than a representation of reality. They should realize that a computational model can serve as a source and tool for theoretical learning based on physical principles and concepts, even when they do not directly correspond to reality. Furthermore, students should recognize that the model can be used to design and verify physics theories. The lack of results for *Nature*, Level III, is likely because such aspect-specific reasoning is not part of the upper-level pre-university physics curriculum in the Netherlands. Additionally, all the students interviewed were in the penultimate year before their final exams. It is possible that the concept associated with *Nature*, Level III, may have been addressed in a later stage.

To be evaluated for Level III within the *Multiple* aspect, which involves describing phenomena from different physical perspectives, students must be able to explain how various physics computational models can be used to illuminate a physical phenomenon from different perspectives. Additionally, students must articulate how these computational models complement one another in understanding physical phenomena. For example, radioactive decay can be described from several perspectives, such as using empirical data, activity, and dose, as well as from the standpoint of nuclear physics, which describes the interactions between nucleons. Level III within the *Multiple* aspect may not be achieved because having or using such perspectives is not required for upper-level pre-university students in the Netherlands. Typically, students are exposed to only one theory in a given physics context, so, unsurprisingly, *Multiple*, Level III, has a score of zero.

Based on the results of this study, we found that Level II within the *Changing* aspect (Alterations due to new findings of the original computational model) and Level III within the *Changing* aspect (Alterations due to findings from computational model experiments) are relatively similar. Level II within the *Changing* aspect involves understanding how a computational model can be changed when new findings about the model itself become available, for example, concerning its structure, assumptions, or behavior. In contrast, Level III involves understanding how a computational model can be modified when findings from computational model experiments yield new insights into the physical phenomenon under investigation. This distinction presupposes a clear understanding of what counts as findings about the model itself versus findings about the phenomenon as inferred through model experiments, as well as what is meant by conducting experiments with a computational model, a distinction that is central to epistemic accounts of modeling competence (Upmeier zu Belzen et al., 2019). However, these distinctions are conceptually subtle and not consistently clarified in the existing literature. As a result, the boundary between *Changing*, Level II and *Changing*, Level III may not have been sufficiently explicit in the framework's operationalization. This lack of clear differentiation could explain why students articulated reasoning corresponding to *Changing*, Level II relatively frequently, while no utterances were identified at *Changing*, Level III.

This study focused exclusively on students' utterances about meta-modeling knowledge, which aligns with the content of the FCMC. During the interviews, no explicit questions were asked about technical modeling skills, such as programming skills or the use of specific computer modeling software. Previous research distinguishes between conceptual modeling competence and technical-procedural skills (Grünkorn et al., 2014; Schwarz et al., 2009). Although the two domains often complement each other in practice, this study shows that the student utterances analyzed in the field of meta-modeling knowledge are largely independent of students' prior technical experience with computational modeling. Some interviewed students had prior experience with computer models, while others had relatively little or no experience. Nonetheless, all interviewed students could make reflective and meaningful utterances about the nature, purpose, and validity of computational models, as well as their scientific importance. This underlines that possessing technical skill does not guarantee a developed epistemological understanding of models (cf. Magana et al., 2024; Weber & Wilhelm, 2020). This finding aligns with Giere's (2004) pragmatic perspective, in which it is not the model itself that carries meaning, but its purposeful use by the user. In line with this, the student utterances in this study are interpreted as manifestations of underlying competences in meta-modeling knowledge, regardless of prior software expertise or experience with computational modeling tools.

The two research questions are not entirely independent. Suppose students are incapable of reasoning about computational models at a certain level. In that case, there will be a lack of quotes at that level, removing the opportunity to gauge them. This happened for Level III of *Nature, Multiple* and *Changing*. The overlap between RQ1 and RQ2 highlights a key challenge in interpreting the results: the interdependence of framework applicability and student performance. This interplay complicates distinguishing between framework limitations and genuine gaps in students' meta-modeling knowledge. It should be noted that, despite carefully compiling the content of the FCMC, the literature on meta-modeling knowledge for computational modeling does not yet provide sufficient guidance. This study may help address the issue and could contribute to the field of computational modeling for researchers in physics education and related fields, as well as for physics and science teachers.

Generally, upper-level pre-university students who have chosen physics as their subject are exposed to computational modeling relatively late in their school careers (Basu et al., 2016; Heck, 2015; Musaeus & Musaeus, 2024). Therefore, their meta-modeling knowledge of computational modeling has not yet reached a sufficiently abstract level. Presumably, for this reason, their scientific reasoning regarding computational modeling is not yet sufficiently developed. This could be why the FCMC aspects *Nature*, *Multiple*, and *Changing*, all level III, have no scores. The absence of Level III reasoning within these aspects may also stem from a limited emphasis on abstract reasoning and metacognitive skills in the curriculum. Students often engage with pre-designed models rather than constructing or refining their own, limiting opportunities to develop higher-order meta-modeling skills. The distinction between Level II and Level III within the *Changing* aspect requires further theoretical clarification to better evaluate and support students' understanding of the scientific rationale for model modification.

From an instructional perspective, the absence of Level III reasoning in several aspects suggests that students may require more explicit opportunities to engage with models as epistemic tools rather than as representational or computational devices. Tasks that invite students to use models to generate hypotheses, compare alternative modeling assumptions, or explore the consequences of modifying model structures could support the development of Level III understanding. In addition, instructional sequences in which computational models are revisited across contexts, rather than introduced as isolated tools, may help students perceive models as resources for theorizing and inquiry. Importantly, such tasks would need to foreground the roles, purposes, uses, and limitations of computational models and the modeling process, rather than focusing solely on computational correctness (Campbell & Oh, 2015; Passmore et al., 2014; Rost & Knuutilla, 2022).

This study addresses an identified gap in the science education literature, namely the lack of an analytic framework specifically suited to examining students' meta-modeling knowledge in the context of computational modeling. While previous frameworks and studies have primarily focused on modeling in general science or on conceptual models (Göhner et al., 2022; Upmeier zu Belzen et al., 2019), they offer limited guidance for analyzing students' reasoning about computational models. By adapting the epistemic structure of the Framework for Modeling Competence (Göhner et al., 2022; Upmeier zu Belzen et al., 2019) to the domain of physics computational modeling, this study advances research on model-based learning by providing a domain-specific framework for analyzing students' meta-modeling knowledge. The resulting Framework for Computational Modeling Competence offers a basis for examining students' reasoning about computational models across multiple grade levels and instructional contexts.

Conclusion

Our results indicate that the Framework for Computational Modeling Competence (FCMC) effectively categorizes students' utterances, revealing varying levels of meta-modeling knowledge in computational modeling. While students demonstrated a solid understanding of the *Purpose* and *Testing* aspects across multiple levels, they struggled to achieve the expert level of understanding of the *Nature*, *Multiple*, and *Changing* aspects. This suggests that students' meta-modeling knowledge appears well developed in applied contexts and empirical settings, but less advanced in abstract and theoretical reasoning. This underscores the importance of fostering higher-level reasoning across aspects of computational modeling.

The findings of this study significantly enhance our understanding of how students perceive and engage with computational modeling in physics education, aligning with research in science education that emphasizes the importance of fostering students' understanding of computational models beyond technical proficiency (Grosslight et al., 1991; Schwarz & White, 2005). Existing literature highlights a gap between technical and process skills and deeper epistemological insights, often observed when students engage with pre-designed models rather than constructing and refining their own (Louca & Zacharia, 2012). Our findings substantiate this by showing that most students achieved Level II understanding in the *Nature*, *Multiple*, and *Testing* aspects, but rarely reached Level III understanding. This indicates that despite students having a relatively strong understanding of modeling as a scientific activity, they struggle to utilize models as tools for theoretical exploration and hypothesis testing, a core competence in scientific inquiry, and thus lack a deeper understanding of computational modeling as a scientific activity (Hestenes, 1987; Schwarz et al., 2009; Windschitl et al., 2008). It is therefore desirable that teaching approaches focus more on these aspects of computational modeling in physics education. Computational modeling should be introduced to students when they first encounter physics, and integrating it into physics teaching in a more philosophical and hypothetical manner is essential to what we want to teach students (Koponen, 2007; Windschitl et al., 2008).

The FCMC proposed in this study provides a suitable tool for assessing students' understanding of computational modeling in an educational context. This study contributes to the international science education literature by offering a structured approach to evaluating students' meta-modeling knowledge in engaging with computational models and their epistemological grasp of modeling as a scientific practice. This emphasis on meta-modeling knowledge aligns with calls for competence-based education in science (Constantinou et al., 2019; Koponen, 2007).

Limitations and future directions

Despite the relatively large amount of interview data collected, this study has some limitations. First, the population studied is relatively small: 36 upper-level pre-university students. This student's grade was chosen because they have more prior knowledge of basic physics than students who have just started taking physics classes and are thus better able to reason about the physics concepts on which the computer models are based. Second, the students' findings from the interviews were based on two computer models, each focusing on a different topic in physics: falling motion (with and without air resistance) and radioactive decay. These topics are typically introduced early in the physics curriculum, ensuring that the interviewed students' prior knowledge is generally consistent across schools. Therefore, the computer models, while representative, may not fully capture the range of modeling demands required across different physics concepts and contexts.

A significant limitation of this study is the interdependence between framework validation and student performance. The absence of Level III reasoning regarding the aspects *Nature*, *Multiple*, and *Changing* may reflect either limitations in the framework's ability to capture abstract elements or a lack of exposure to computational modeling in the current curriculum. This ambiguity limits the generalizability of findings and underscores the need for further empirical validation of the framework in physics education research and related fields.

An alternative interpretation of the limited occurrence of Level III reasoning concerns the interview methodology itself. While semi-structured interviews allow for in-depth probing of students’ reasoning, they may not always elicit the full extent of students’ epistemic understanding, particularly for forms of reasoning enacted through extended modeling activities rather than verbal reflection. It is therefore possible that some students possess elements of Level III understanding that were not fully articulated during the interview. Future studies could combine interviews with task-based or classroom-based data to further explore this possibility.

This study highlights the importance of the FCMC in evaluating students' ability to apply computational models in physics education. The framework effectively categorizes responses and identifies areas of strength. Yet it also highlights persistent gaps in students’ higher-level reasoning across aspects, particularly their ability to use models as dynamic tools for theoretical exploration, scientific activity, and scientific reasoning. To address these gaps, educators should integrate computational modeling as a core element of physics curricula, emphasizing its epistemological and abstract dimensions. Instructional strategies, such as scaffolding computer modeling activities that involve theoretical learning based on physics principles and concepts, and comparing and testing multiple computational models, can help students progress beyond procedural applications to achieve Level III reasoning. At this level, students use computational models to theorize, generate hypotheses, and analyze phenomena from multiple perspectives, fostering a deeper conceptual understanding and promoting authentic scientific inquiry.

Future research should explore how targeted interventions and expanded frameworks can further support students in mastering advanced forms of computational modeling reasoning. More educational research on computational modeling and the competencies involved is essential to more deeply embed computational modeling into physics education and cultivate scientifically literate students capable of engaging in complex, hypothesis-driven inquiry (Phillips et al., 2023; Sabelli, 1994). Beyond physics, computational models are also used in other disciplines, such as chemistry, biology, and economics (Husen & Chowdhury, 2023; Musaeus et al., 2024). Given their central role across many scientific fields, a thorough understanding of the nature, applications, and limitations of computational models is crucial for students' scientific literacy (Feinstein, 2011; Lederman et al., 2023).

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