Science Teachers' Attitudes towards Computational Modeling in the Context of an Inquiry-Based Learning Module

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Abstract

This study focuses on science teachers' first encounter with computational modeling in professional development workshops. It examines the factors shaping the teachers' self-efficacy and attitudes towards integrating computational modeling within inquiry-based learning modules for 9th grade physics. The learning modules introduce phenomena, the analysis of measurement data, and offer a method for coordinating the experimental findings with a theory-based computational model. Teachers' attitudes and self-efficacy were studied using survey questions and workshop activity transcripts. As expected, prior experience in physics teaching was related to teachers' self-efficacy in teaching physics in 9th grade. Also, teachers' prior experience with programming was strongly related to their self-efficacy regarding the programming component of model construction. Surprisingly, the short interaction with computational modeling increased the group's self-efficacy, and the average rating of understanding and enjoyment was similar among teachers with and without prior programming experience. Qualitative data provides additional insights into teachers' predispositions towards the integration of computational modeling into the physics teaching.

Keywords Computational modeling · Programming · Physics education · Inquiry-based learning

Introduction

AI Harrison. "Maybe we've been thinking about this all wrong"

Paul Stafford, "How's that"?

AI - "Maybe it's not new math at all"

Katherine Johnson – "It could be old math, something that looks at the problem numerically and not theoretically... Math is always dependable" AI - "For you it is." (leaving the room)

Katherine – "Euler's method!"

Paul – "Euler's method? But that's ancient!"

Katherine – "It is ancient, but it works..."

(Scene from Theodore Melfi's film "Hidden Figures," 2016).

This excerpt describes the breakthrough of the NASA team working on the calculation of the re-entry coordinates for John Glenn's first orbital flight outside the atmosphere. When faced a problem that cannot be solved analytically, Katherine Johnson, the woman who worked as the team "calculator," suggested to use the Euler method—a step-by-step calculation for solving the differential equations of motion (Develaki 2019). Today, the Euler method is implemented in computer models that are investigated in introductory physics courses (e.g., Chabay and Sherwood 2008) and allows educators to expand the scope of problems that students can tackle.

Developing and using computational models reflects an important goal for K-12 science education, within a range of scientific practices such as designing and employing experimental investigations, analyzing measurement data and communicating them (NRC 2012). Indeed, there is growing evidence for doing classroom inquiry that entails a dual focus on experimental measurement and computational modeling in primary and secondary schools (e.g., Farris et al. 2019; Fuhrmann et al. 2018). The extent to which teachers adopt inquiry-based science teaching practices may be related to their views of inquiry learning (Lotter et al. 2007; Osborne

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2014; Blanchard et al. 2009), their subject matter knowledge (Tseng et al. 2013) and their teaching self-efficacy (Lakshmanan et al. 2011). However, research on teachers' attitudes towards integration of computational models in the context of experimental investigations is scarce (Gerard et al. 2011), and thus, teachers' implementation of instruction that involves *both* experimental classroom inquiry and construction of computational models, remains an open field of research.

In this paper, we describe science teachers' engagement with inquiry-based curricular modules for 9th grade physics that introduce computational models. The modules include a structured, inquiry-based experimental component, and a theoretical component in which computational models are used to verify the experimental observations. Drawing on studies that address teachers' attitudes and self-efficacy as indicators for implementation of inquiry teaching, we ask how do teachers' prior experiences in teaching physics influence their self-efficacy and attitudes towards inquiry-based learning practices? Specifically, in relation to computational modeling, we ask how does teachers' prior involvement with programming influence their self-efficacy in, and experience of computational modeling?

Literature Review

Coordinating Theory and Experimental Evidence: a Model-Based Perspective

A scientific investigation integrates two endeavors: the formation or revision of predictive theoretical constructs and the design of experiments that produce reliable observations or measurements (Klahr and Dunbar 1988). In studying the development of scientific practices among students, researchers can focus on practices of experimental design such as the selection and control of variables (Chen and Klahr 1999) or the evaluation of measured data (Allie et al. 1998; Kanari and Millar 2004), or they can study how students use and conceptualize theoretical ideas. In practice, the two activities are difficult to separate. Specifically, unsubstantiated hypotheses, or "implicit theories" (Kuhn 2011) have a strong influence on students' planning and interpretation of experiments. Conversely, flawed experimental design, or misinterpretations of measurements can shape theoretical misconceptions. Judging experimental results as implausible in light of learners' "naïve" theories is a crucial aspect of the theory-experiment interaction (Kuhn 2011).

In many introductory college and high school courses, the interaction between theory and experiment plays out in structured labs designed to "prove" or concretize theoretical statements. Although the purpose of these labs is to substantiate the theory students learn in lecture courses, studies show that they do not contribute to students' content knowledge, as measured by test performance (Holmes and Wieman 2018). Moreover,

students' perceptions of their own expertise in conducting experiments tend to decline during such structured laboratory courses (Wilcox and Lewandowski 2018).

An alternative is the inquiry or design lab that entails discovery experiments that *extend* the theoretical knowledge students acquired in prior learning. For example, in the Investigative Science Learning Environment (ISLE) curriculum (Etkina et al. 2006a), students design experiments to develop and then test model-based explanations of observed phenomena. This approach brings the design of experiments and the analysis of measurement data to the fore, and often challenges students' prior knowledge. To do so, an extended amount of time is allocated to judging the reliability of measurement data. Educational research shows that in these transformed labs, there is no decline in students' perceptions of their expertise in conducting experiments as in the structured lab (Wilcox and Lewandowski 2018).

A specific case of coordinating theory and experiments is the construction and evaluation of models. Models are simplified, and often abstracted quantitative representations of the system under investigation, constructed to describe, explain or predict the system's behavior (Etkina et al. 2006b). In introductory physics courses, models are usually instantiations of general, theoretical principles such as Newton's laws, in generic systems such as orbital motion under the influence of a centripetal force (Halloun and Hestenes 1987). Recently, researchers who design upper-level laboratories, suggested a new modeling framework, in which model construction, evaluation and revision is utilized for two inter-connected modeling cycles: the measurement model cycle and the theoretical model cycle (Zwickl et al. 2015; Dounas-Frazer and Lewandowski 2018). This framework provides two possible reactions to a misalignment of theory-based model and measurements: revising the measurement model—the instruments used or the interpretation of the measurement data, or, revising the theoretical model. While this framework has been suggested for upper-level undergraduate labs that often involve sophisticated measurement equipment, it is a useful construct for guiding scientific investigations at various levels. It suggests designing investigations with explicit awareness to both the judgment of measurement data, and to the limitations of the theory-based, physical system models. The measurement and/or the theoretical models can be revised to achieve better alignment of theory and the behavior of the actual physical system. While most examples of theoretical system models are mathematical/analytical (e.g., Dounas-Frazer and Lewandowski 2018), these models can be also realized using computer simulations, as we will show below.

Constructing Computational Models vs. Using Readymade Ones

Using readymade computational simulations in science classrooms is a widespread practice (e.g., De Jong et al. 1999; De

Jong et al. 2013). In this approach, students manipulate parameters of the simulated system to learn about its mechanism. The simulations are introduced as substitutes of the real system and the interaction with them resembles a structured laboratory experiment. For example, students investigate a simulation of collisions and compare the velocities before and after the collision to deduce the law of conservation of momentum (De Jong et al. 1999). A different educational approach is to engage students in constructing the computational model (VanLehn 2013; Wagh and Wilensky 2018). Engaging in model construction requires learning environments that allow students to add or change model features. The students need to plan how to add or change certain aspects of the model, and then run the computational model and compare the outcome vis-à-vis other realizations of the theory or experimental results. For example, in a computational model of a falling paratrooper, students decide whether the magnitude of the drag force depends on the velocity or not. They then examine whether their definition of the drag force yields a velocity pattern that reaches a relatively low terminal velocity as expected (Develaki 2017).

Constructing computational models and especially accessing their code has been explored in secondary school physics (Aiken et al. 2013; Sherin et al. 1993; Langbeheim et al. 2019; Hutchins et al. 2020), and in a few introductory college texts (Redish and Wilson 1993; Chabay and Sherwood 2008; Orban et al. 2018). However, there are only few examples of using simulations side by side with experiments. For example, Farris et al. (2019) investigated how 4th graders learn the concepts of speed and acceleration by measuring the motion of toy cars and building models of motion in a computational environment. Despite its basic level of content, this study shows that even young students are able to think about variations in measurement, and relate real-world observations to computational models. Similarly, in Fuhrmann et al. (2018) students studied the osmosis of sugar water through an egg membrane experimentally and then explored a computer, particle-based model that mimics the experimental results. They found that both exploring a ready-made model and designing a model in this approach foster the development of conceptual knowledge about the topic. However, only actively designing the model results in developing nuanced understanding of the role of models in scientific investigations. This finding emphasizes the epistemic importance of constructing models, compared to just exploring them.

Engaging students in building computational models reflects the actual practice of scientists (Develaki 2017; Winsberg 2010) and contributes to the development of creativity and computational thinking (Hutchins et al. 2020; Popat and Starkey 2019). However, letting students construct models, and especially when construction involves the understanding and manipulation of computer code, is a much greater leap for educators. In order to guide students in

understanding and modifying code, teachers need to become proficient in programming themselves and to produce new learning materials for their science and mathematics classrooms. This requires teachers and students to transition from being *users* of computer programs to being *builders* of programs, which can be viewed as a substantial change in computing culture (Ben-David Kolikant and Ben-Ari 2008) or an educational paradigm shift (DiSessa 2001).

Teachers' Self-Efficacy in Inquiry-Based Teaching

Implementing inquiry-based teaching that involves designing experiments, interpreting measurement data, and constructing models is challenging. In this study, we consider two main factors that determine the extent to which teachers implement such teaching in their classrooms: (1) teachers' self-efficacy in teaching the subject matter (e.g., Lakshmanan et al. 2011); (2) teachers' attitudes regarding inquiry-based learning and their beliefs in its effectiveness (Blanchard et al. 2009).

Self-efficacy is a set of beliefs regarding one's capabilities to perform well in a certain field (Bandura 1997). These beliefs are one of the main driving forces that motivate people to put effort and pursue challenging tasks. Self-efficacy beliefs are dynamic, especially during learning of new skills, or beginnings of new professional endeavors. In preliminary acquisition of an expertise, there are several factors influencing self-efficacy, such as observing others demonstrating successful performances, and most importantly, one's own mastery experiences. Mastery experiences are successful performances of tasks, such as conducting an effective lesson or lesson sequence. Teaching self-efficacy determines teachers' beliefs about their competence and performance in teaching (Tschannen-Moran et al. 1998). Teachers' years of experience in teaching are significantly correlated with their teaching self-efficacy (Tschannen-Moran and Hoy 2007) but not with their tendency to implement inquiry-based teaching (Marshall et al. 2009). Although physics is considered a challenging topic, studies of self-efficacy of teaching physics are very rare (e.g., Tanel 2013).

The second factor influencing implementation of inquiry-based teaching is teachers' beliefs regarding the importance and fruitfulness of this type of teaching. Teachers' who were less inclined to believe that inquiry-based teaching methods lead to effective student learning were less likely to implement them in their lessons (Lakshmanan et al. 2011). Similarly, teachers who had meaningful views of the pedagogical approaches to inquiry, grounded in learning theories, were more likely to adopt inquiry-based learning practices in their classrooms (Blanchard et al. 2009).

Reformed teaching pedagogies and curricula are usually introduced in professional development (PD) workshops, so that successful implementations can be related to the teachers' backgrounds and/or to the PD process. The structure, duration,

and content of PDs is an important factor influencing the implementation of reformed instruction and curricular innovations. A survey study showed that PDs that focus on content knowledge and provide opportunities for active learning have the strongest positive effect on teachers' self-reported increase in knowledge and skills (Garet et al. 2001). Moreover, PDs that include mastery experiences have the strongest effect on teachers' self-efficacy (Tschannen-Moran and McMaster 2009) and consequently on classroom implementation (Penuel et al. 2007). There are only few examples of teacher training programs that include computer programming (e.g., Repenning et al. 2020). Such courses are necessary for boosting their self-efficacy in computational modeling and knowledge of computational thinking (Papadakis and Kalogiannakis 2019).

Scope of the Current Study

A growing number of studies indicate that elementary and secondary school students are able to construct computational models and to modify their code in the context of physics (e.g., Aiken et al. 2013; Langbeheim et al. 2019; Farris et al. 2019), but less is known about the views of in-service science teachers regarding adopting computational modeling that involves manipulation of computer code. Therefore, the goal of this study is to examine science teachers' attitudes towards introducing computational model construction in the context of inquiry-based learning in physics. Our main research questions are:

1. How do teachers' prior experiences in teaching physics influence their self-efficacy and attitudes towards inquiry-based learning practices in a PD workshop?
2. How does teachers' prior involvement with programming influence their self-efficacy in, and experience of computational modeling that involves coding in a PD workshop?

We investigated these questions in the context of workshops that introduced two curricular modules for 9th grade physics: The focus of the first is the oscillations of a spring-mass system, and the focus of the second is free-fall with air-drag. Each module begins with experimental investigations of motion patterns, and concludes with a theoretical section that compares the experimental measurements to the output of computational models.

Experimental Section of the Learning Module

The experimental section of both modules comprised six 90-min lessons that are summarized in Table 1. The lessons are based on the following design guidelines:

- a) Capturing student attention—the main purpose of initial lessons is to raise attention to aspects of the phenomenon

through problematization (Reiser 2004; Phillips et al. 2017). In the first module, the theoretical exploration focuses on the “peculiar” lack of covariance of the period of the oscillating spring system and its amplitude. In the second, it focuses on the apparent discrepancy between the Aristotelian view (that mass influences the falling rate of objects) and the Galilean view (that it does not).

- b) Scaffolding measurement and data analysis practices—the measurement and data analysis methods are introduced in a guided manner in the initial lessons. In subsequent lessons, the teacher removes some of the direct instructions: first in asking students to plan and justify an experimental design to answer a common research question (e.g., how does the falling rate of paper cups change when increasing its mass?) and then in planning and justifying an experimental design to study a question that students generate by themselves (see Table 1 for examples)
- c) Raising student accountability—students build an evaluation rubric for experimental investigations based on fabricated student reports, in order to develop awareness for reporting standards. Then, they share their evaluation criteria to produce a unified rubric. Finally, they use the consensus evaluation rubric to provide feedback on the presentations of their peers.

After completing the experimental section, and sharing their inquiry projects using posters or presentations, the students proceed to study a theoretical model of the phenomenon. The theoretical section includes a qualitative, conceptual section and the quantitative computational section.

Qualitative Theoretical Modeling

The qualitative, conceptual section comprises two lessons in which students construct a paper and pencil theoretical model that explains the phenomenon that they investigated experimentally. For example, in the oscillating spring-mass unit, students analyze the trace of the oscillating mass, using motion patterns produced by the Tracker video analysis software (Brown and Cox 2009). Their analysis leads to the discovery that the maximal speed of the mass corresponds to the amplitude, or the distance covered by the mass during one period of oscillation. This finding is used to hypothesize *qualitatively* that the length of the motion path and the average speed of the mass cancel each other out, and therefore, their ratio—the period of one oscillation—is constant.

Quantitative Computational Modeling

The purpose of the final unit in the module is to introduce a quantitative approach for comparing the measurements and the theory-based model. The analytical equations of motion

Table 1 Experimental component of the gateway to physics modules

Purpose of lesson	Oscillations module	Free-fall module
1. Initial exposure to phenomenon	What is an oscillation of a spring? What role do springs play in oscillating systems?	Does the mass of an object influence its falling rate? The dispute between Aristotle and Galileo
2. Initial problematization of measurement	How to measure the period of oscillation of a mass on a spring when the motion fades?	Why does the mass of paper cups influence their rate of falling whereas the mass of clay balls does not?
3. Joint investigations: drawing conclusions despite measurement uncertainties	Students systematically investigate the influence of amplitude on the period of oscillation of the mass-spring system	Students systematically investigate the differences between falling rates of paper cups, while increasing their mass, and discover that the differences decrease with mass
4. Developing an evaluation rubric	Students were given an empty evaluation rubric and three fictitious student reports. They suggested categories, and differentiated between performances on each category.	
5. Parallel open investigations	Students chose a research question related to the period of oscillation of a spring mass system (e.g., what happens when increasing the suspended mass), suggested hypotheses and built an experimental setup to test their hypotheses.	Students chose a research question related to falling motion (e.g., how does the diameter of a balloon influence its falling rate), suggested hypotheses and built an experimental setup to test their hypotheses
6. Peer evaluation	Students present their posters/presentations to their peers, and peers provide written or oral feedback based on the evaluation rubrics.	

of both processes we discussed—harmonic oscillations and falling with a drag force—are nonlinear and involve mathematics beyond that of 9th grade. In order to overcome the mathematical complexity, we introduced the theoretical model using a computer program that calculates the trajectory using the Euler method (Cromer 1981; Develaki 2019). The computational models of motion with air drag and of the oscillating spring-mass systems were realized using trinket.io—a free, online tool for building coding activities and courses. We chose this platform, since it runs Vpython—a 3D graphical package for python (Scherer et al. 2000). Python was chosen since it replaced introductory level programming languages that were used in the past such as Pascal, BASIC, and Fortran. Figure 1 illustrates the trinket interface that has the code on the left side and the graphic output on the right. The unit introduced all the necessary programming ideas so that students (and teachers in the PD workshop) were not expected to have prior experience with VPython. The supplementary material provides detailed information on the introduction of the computational model.

The Euler method presents the theoretically predicted motion pattern using three linear equations, calculated repeatedly every time step. The first equation calculates the net force according to the current location or velocity of the object; the second calculates the new velocity of the object, based on Newton's 2nd law; and the third updates the location of the object based on the new velocity. For example, the implementation of these three equations for the falling with air drag problem is shown in lines 14–16 of the code shown in Fig. 1. In addition to using relatively simple linear equations, this approach promotes the analysis of the dynamics of *specific*

moments during objects' motion patterns, thereby facilitating the comprehension of the process as a whole (Sherin et al. 1993; Sherin 2001).

Methodology

Context and Research Questions

The two modules were introduced in two summer PD workshops that span four full days and a total of 30 hours of contact. The workshops included an overview of the principles of inquiry-based learning, engaging in measurement cycles and in coordinating the experimental results with the computational model. The workshops were advertised as introducing inquiry for 9th grade physics, and did not as present themselves as focusing on computational modeling. The first 2 days of the PD focused on experimental investigations, and the last 2 days focused on the related theory and computational modeling. Teachers worked in small groups and shared their experiences in discussions with the rest of the participants and the workshop instructors. Of 49 participating teachers, 41 completed all of the activities. Within this group, 26 teachers are considered “experienced teachers”—teachers who taught physics at the 9th grade level for at least 3 years, or at the high school level for at least 1 year (high-school teachers usually come with a bachelor in physics, and teach more physics in 1 year than 9th grade science teachers do in 3 years). Fifteen teachers were considered “novice teachers,” if they taught physics in 9th grade for less than 3 years. Three years is a common cutoff for differentiating experienced and novice teachers in educational research (e.g., Tschannen-Moran and Hoy 2007). This

Fig. 1 Vpython code of the computational model (left), and graphical interface (right). The code includes two definitions of graphical objects: the “box” (line 9) which imports the motion diagram of the real object (marked in red dots) and a green sphere (defined as “s” in line 10) which moves according to a computational model. The green trace of the sphere is compared to the red pattern of dots that was produced from a video of a falling paper clip using the Tracker software

group consisted of new teachers, and a few experienced teachers in other fields such as math, who were new to teaching physics topics.

Data Collection and Analysis

The first research question asked how do teachers' prior experiences in teaching physics influence their self-efficacy and attitudes towards inquiry-based learning practices in a PD workshop. To examine this question, we used the following data sources:

- 1a. Physics teaching self-efficacy survey—Before the workshop, we administered a self-efficacy survey with six Likert-scale items of the same format: “I am confident in teaching quantitative problem solving/ introducing computational models/ textbook experiments, in 9th grade physics” on a scale of 1 to 5 (5 = strongly agree, 4 = agree, etc.) and a background survey indicating years of experience in teaching physics and experience in computational modeling. The internal consistency of the self-efficacy scale was high—Cronbach $\alpha = 0.85$.
- 1b. Workshop appreciation survey—At the end of the workshop, we administered a feedback survey with six five-point Likert-scale items such as “The workshop contributed to my ability to explain fundamental concepts such as Newton’s 1st law/ textbook experiments etc.” (strongly agree, agree, etc.) and open-ended items asking to state aspects of the workshop that they found significant and aspects that were lacking.
- 1c. Attitudes towards physics lab goals—We administered a 15-item survey to evaluate teachers’ beliefs about the goals their students should achieve in the physics lab. Some of the items were adapted from the E-CLASS - Colorado Learning Attitudes Science Survey for

Experimental physics, (Wilcox and Lewandowski 2018). The E-CLASS includes items such as “The primary purpose of doing physics experiments is to confirm previously known results (strongly agree, agree etc.)”. Our adapted version was: “Rate the following statements representing goals for students to achieve in the physics lab: *to confirm the theory discussed in class.*” This statement reflects a common goal for the structured lab, while statements such as “*to acquire tools for evaluating the work of peers*” represents a goal of an inquiry-based lab. The survey utilized a 4-level Likert scale. We used exploratory factor analysis to aggregate fifteen statements into two categories: (a) goals of inquiry-based laboratory practices, (b) goals of structured laboratory practices. The full list of items, the corresponding categories and internal consistency scores are shown in Table 2.

2. In order to investigate the 2nd research question regarding the influence of teachers’ prior involvement with programming on their self-efficacy in, and experience of computational modeling that involves coding in a PD workshop, we used the following data sources:

- a. Programming self-efficacy—Before and after the computational modeling activity we administered a self-efficacy survey with three five-point Likert-scale items such as: “I think I can understand / write and modify computer code” (strongly agree, agree, etc.). Thirty-eight teachers responded to the pre and post self-efficacy items related specifically to the computational modeling activity. The internal consistency of the self-efficacy scale was substantial—Cronbach $\alpha = 0.76$, but the distribution of the ratings in the posttest was not normally distributed (Shapiro-Wilk $W = 0.94$, $p = 0.03$)

Table 2 The grouping of the items regarding the goals of the physics lab

Category	“Rate the importance of the following statements representing goals for students to achieve in the physics lab”	Cronbach’s α (pretest)	Cronbach’s α (posttest)
(a) Inquiry-based laboratory goals	“An active, hands-on acquaintance with physical systems” “Acquire tools for evaluating the work of peers” “Acquire tools to improve group work” “To present and report findings to peers (using presentations/posters)” “To identify sources of measurement error” “To make inferences from experimental findings” “To learn to improve the experimental setup to increase measurement accuracy” “To design an experimental setup to investigate the quantitative relation between two variables”	0.82	0.79
(b) Structured laboratory goals	“To illustrate and concretize the theory discussed in class” “To learn to write reports of experimental findings” “To confirm the theory discussed in class” “To learn methods for analyzing and presenting data” “To understand the role of experiments in building theories” “To work with the safety regulations related to equipment and materials in the lab” “To search and find information sources” (relevant to the experiment)	0.64	0.81

- b. Programming activity appreciation—Three statements addressed specifically the coding activity “The coding activity was interesting,” “The coding activity improved my understanding of the physics of the spring-mass system / free-fall with drag,” “I understood everything I did in the coding activity” (strongly agree, agree, etc.). The internal consistency of the activity appreciation scale was substantial—Cronbach $\alpha = 0.74$.

The full survey can be found in the [online supplement](#). In addition, we used transcripts from the activity itself to corroborate our survey findings.

Findings

Physics Teaching Self-Efficacy

The self-efficacy related to teaching physics in 9th grade was relatively high before the workshop with an average rating of 3.91 out of 5. The average ratings of the novice teachers with less than 3 years of teaching was 3.566, and the experienced teachers average rating was 4.10. This difference is significant ($t = -2.56$, $p = 0.017$).

Teachers’ Overall Appreciation of the PD

The characterization of teachers’ perceptions of the contribution of the workshop was based on two forms of data: Likert-scale ratings and open-ended questions. The average ratings

were calculated and analyzed according on the teachers’ experience as shown in Table 3. Both groups rated the contribution of computational modeling (item 6) and designing the experimental setup (item 3) higher than the rest of the topics. The contributions to two common aspects of teaching—conducting standard textbook experiments (item 2) and clarifying fundamental physics concepts (item 5)—were rated higher by the novice teachers, and these differences were marginally significant. In the other categories, the differences between the experienced and novice teachers were very small. Also, an index measure, combining all of the items, reveals no significant difference among groups ($t = -0.146$, $p = 0.88$) and between workshops ($t = -1.21$, $p = 0.23$).

The responses to the open question, corroborate these findings. For example, in their suggestions for two or more aspects of the workshop that contributed to their teaching, Vera, an experienced teacher wrote:

The inquiry-module for ninth grade, structured and original, will greatly facilitate my work next year. I learned to use Excel for analyzing an experimental graph and fitting it to an equation.

Whereas Ana, a novice teacher in her first year wrote:

The main contributing aspects were the parallel investigations, the discussions about classroom inquiry, its meaning and its implementation. Also, the acquaintance with the step-by-step method using the software (although I’m not sure I would implement it in class).

Table 3 Teachers' average rating of the contribution of the workshop to their teaching

The workshop contributed to my ability to:	Experienced (<i>N</i> = 26)	Novice (<i>N</i> = 15)	Sig. (Wilcoxon signed)
1. Teach physics problem solving	3.38 (1.3)	3.07 (1.1)	$p = 0.28$
2. Conduct common textbook experiments	3.31 (1.2)	3.73 (0.9)	$p = 0.11$
3. Conduct experiments that engage students in designing the experimental setup	4.04 (0.9)	4.00 (1.2)	$p = 0.99$
4. Conduct open experiments that students plan based on their own research questions	3.88 (1.14)	3.40 (1.1)	$p = 0.21$
5. Explain fundamental concepts such as Newton's 2nd law, Hooke's law	3.31 (0.9)	3.73 (0.9)	$p = 0.08$
6. Use simulations to construct a theoretical explanation for experimental findings	3.96 (1.0)	3.73 (1.1)	$p = 0.505$
Overall	3.61 (0.8)	3.65 (0.75)	$p = 0.23$

Both teachers mentioned the structured inquiry sequence as a major contribution to their teaching. In relation to the computational tools, Vera mentioned Excel which was used to analyze the experimental data, and Ana mentioned step-by-step computational modeling.

Overall, teachers mentioned five main components of the PD: the two most common topics, both mentioned by 54% of the teachers, were the structured inquiry sequence and/or the computational modeling activity. In addition, 41% mentioned the measurement error analysis and/or the active learning format of the workshop. Finally, 24% of the teachers mentioned the contribution of the workshop to their understanding of fundamental physics concepts.

Attitudes towards Laboratory Practices

The differences in attitudes towards laboratory experiments before and after the PD were relatively minor as shown in Table 4. The teachers' rating of the importance of lab purposes associated with traditional structured lab (category b.) decreased during the workshop, and goals related to inquiry practices have slightly increased. However, a closer examination shows that these differences were not the same across groups. The ratings of inquiry lab goals among novice teachers increased, whereas the experienced teachers' ratings slightly decreased. This difference is marginally significant ($p < 0.1$).

Table 4 Ratings of goals for laboratory experiments (on a scale of 1 to 4)

Category	Pretest M(SD)	Posttest M(SD)	Post-pre difference
a. Inquiry lab goals	3.43 (0.4)	3.48 (0.35)	0.05 (0.33)
b. Structured lab goals	3.64 (0.3)	3.49 (0.42)	− 0.15 (0.29)
Posttest-pretest differences by groups			
Category	Experienced (<i>N</i> = 26)	Novice (<i>N</i> = 15)	Statistical test
a. Inquiry lab goals	− 0.01(0.29)	+ 0.17 (0.37)	$t = 1.71, p = 0.096$
b. Structured lab goals	− 0.15(0.26)	− 0.15 (0.35)	No difference

Teachers' Programming Self-Efficacy

The average rating of programming self-efficacy before the activity was 3.11 (SD = 1.01), and at the end of the workshop, it increased to 3.65 (SD = 0.93). A Wilcoxon signed rank test shows that the difference between pretest and posttest is significant ($W = 930, p = 0.030$). Fifteen teachers stated that they had prior knowledge in programming, and 23 responded they did not. We found significant differences in self-efficacy both pre and post the activity, between teachers that declared to have prior knowledge in programming and teachers who did not. Teachers with prior programming knowledge rated their self-efficacy significantly higher than teachers without such knowledge, both in the pretest ($t = -3.49, p = 0.0013$) and in the posttest ($W = 80, p = 0.0055$).

Teachers' Appreciation of the Programming Activity

A Wilcoxon test shows that appreciation of the coding activity was similar among teachers with ($M = 3.93, SD = 0.55$) and without ($M = 3.46, SD = 1.08$) prior experience in programming ($p = 0.239$). We note that the standard deviation among teachers with no background in programming was larger than among teachers with programming background. This variance is also evident in the boxplot in Fig. 2 (left). A scatter plot of the activity appreciation ratings vs. the self-efficacy of the teachers is shown in Fig. 2 (right). The red circle shows seven

Fig. 2 Appreciation of the activity was similar and positive among both teachers with prior programming experience, and those without (left). Scatter plot of the appreciation and the self-efficacy of the teachers before the activity (right)

teachers with no prior programming experience and low self-efficacy prior to the activity, which gave high rating to the programming activity.

In order to examine the variation in the appreciation of the activity among the teachers without prior programming knowledge, we present excerpts from the activity of two teachers: Vera, an experienced physics teacher with over 20 years of teaching, and Ana, a novice teacher in her first year of teaching. The two teachers were trying to modify the code in the first part of the computational modeling activity (see [online supplement](#)):

V: If I want to do this, and place it (the graphical object) in a different initial location then... (trying to modify the code) It doesn't work. Why didn't it change anything? Oh! What have I done? I erased everything!

A: maybe press here?

V: No, here. But I didn't save, so now what? Start over?

A: No, do this (points to the "remix" button) to go back to the original. That is odd, it leaves the shapes, but not the code...

V: I hate this! I really, really, hate this entire thing. It's annoying.

A: I really like (unclear)

V: I like Excel

A: Excel is really awesome,

V: It is helpful. It is the most convenient tool!

Vera is frustrated with the computational modeling activity because of the technical problem that erased the changes in her code. This incident results in her saying that she "really, really hates this entire thing." Ana, on the other hand, responded with more patience, and even said she likes the modeling activity. They both also agreed that Excel is a useful tool. Vera also rated her appreciation of the activity lower than Ana at the end of the workshop. The following excerpt indicates that while Vera is an experienced physics teaching and very confident with her physics teaching, she is insecure when it comes to computational modeling:

Instructor: how is it going?

V: It's annoying...I cannot compete with them (the students) in this (points to the screen), they will defeat me. Our students learn Python programming in 8th grade...

Inst: But they cannot defeat you in physics...

V: Listen, when I teach them Excel, I am the (authority)...

Vera is afraid that her authority would be undermined by the students who know more programming than she does. Again, she mentions Excel as a software that she is confident in using. Ana, on the other hand, is a new teacher and does not feel the tension between her confidence in teaching physics, and introducing this new task. It also reminds her something she seemed to like as a child.

V: Let's move one

A: Do you remember BASIC? (programming language), "if-then, GOTO" (functions in BASIC)

V: I've heard of it, but never used it

A: When I was 12 years old I was in an afterschool program (that introduced BASIC)

The excerpt shows that Ana had some experience in programming as a child, whereas Vera had none. This minor background detail might also explain their different approaches to computational modeling and indicate the importance of early exposure to computer programming.

Discussion

This study addressed two research questions—the first asked how prior experience in teaching physics influenced teaching self-efficacy and attitudes towards inquiry-based laboratory practices. The findings indicate that prior experience in teaching is strongly related to teachers' self-efficacy of teaching physics. This finding corroborates Bandura's theory that self-efficacy emanates from mastery experiences of performance (Bandura 1997). The significantly higher self-efficacy

in teaching physics of the experienced teachers is also in line with prior research on the effect of experience on teaching self-efficacy (Tschannen-Moran and Hoy 2007). While experience was related to self-efficacy, the overall appreciation of the learning modules was positive among both experienced and novice teachers. This is true for the appreciation of the experimental and computational aspects of the modules, and specifically in relation to the computational modeling activity. Table 3 shows that for the two main aspects of the workshop—computational modeling and conducting structured inquiry (items 3 and 6)—both groups responded similarly, and positively.

The workshops' purpose was to introduce a novel approach for coordinating experimental measurements and theoretical, computational modeling. This approach differs from traditional structured labs that aim at illustrating or reinforcing theoretical concepts. Teachers' decrease in ratings of traditional goals, and the increase in ratings of inquiry practices related to the coordination of experimental results and theory, indicate that the workshop had some influence on the attitudes towards the main goals of the lab. Teachers' ratings of inquiry lab practices such as designing an experimental setup indicate difference between experienced and novice teachers that are marginally significant. The differences may be related to prior acquaintance with inquiry practices: the mastery experience in the workshop might have boosted the novice teachers' belief in the importance of these practices, but not those of the experienced teachers who were already confident. This is similar to the differences in lab ratings of first-year undergraduates and students in more advanced years: first year students had lower initial ratings than students in their second year or beyond (Wilcox and Lewandowski 2018). This difference probably reflects a process of self-selection—students or teachers who persist in their degree or teaching—are more likely to have positive attitudes towards the importance of the practices that they acquired (Wilcox and Lewandowski 2018).

The second research question addressed the relation between prior involvement with programming, self-efficacy, and attitudes towards the computational modeling activity. We found that the self-efficacy related to programming of most teachers has increased during the workshop, although teachers with no programming experience were still less efficacious than the teachers with programming experience at the end of the workshop. In addition, the appreciation of the computational modeling activity was similar among teachers with or without programming experience but the groups differed in the *variation* of their ratings, which was larger among the novice teachers as indicated in the error bars of the boxplot in Fig. 2. The transcript of the computational activity offers an explanation for this variation—it illustrates how two teachers without prior computer programming knowledge reacted differently to the computational activity. The conversation between the two teachers hints that the difference in appreciation may be rooted in different dispositions towards the adaptation

of new technologies: Vera expressed resentment towards the computational modeling activity and contrasted it with her satisfaction with Excel—a user-friendly interface for data visualization that was also used in the workshop. Conversely, Ana mentioned that the programming activity reminds her a positive experience from the past. Vera's reaction reflects the difficulty in switching from the “culture” of computer users of programs such as Excel to the “culture” of computer programmers that requires planning and debugging (Kolikant and Ben-Ari 2008). One way to overcome such barriers is by introducing programming to children at a young age to prevent the perpetuation of the culture focusing on merely using readymade computer artifacts, to a culture views the computer as tool for developing new artifacts (DiSessa 2001). Vera's comments might also indicate that she does not see the value of the computational model. It might be that she could benefit from a framing activity that would explicate the opportunities afforded by the computational modeling activity, and its difference from the Excel. For example, the computational model uses symbols for the variables of force “F” and velocity “v” and allows to perform calculations with them (see lines 14–15 in Fig. 1) this type of representation is not possible in Excel, nor is it possible to simulate motion in a dynamic manner.

Conclusion and Implications

At the beginning of this paper, we referenced the “Hidden Figures” movie scene to introduce the computational Euler method as a legitimate, and sometimes even necessary, substitute for analytical/mathematical modeling. We believe that since computational modeling plays a central and indispensable role in scientific inquiry, this practice needs to be represented in school science, and the only way to do this is by investing in teacher PD. In this study, we examined science teachers' reactions towards a PD workshop that introduced inquiry-based modules with a computational modeling component. We found that the workshop contributed to both experienced and novice teachers. Specifically, we found that most teachers' attitudes towards the computational modeling were positive, and their self-efficacy beliefs regarding computational modeling increased. The main limitation of our study is that it does not describe the actual implementation of the modules by the teachers in their classrooms. This would be a subject for an additional study. Nevertheless, we note that despite the positive reactions at the end of the workshop, only 25% of the teachers implemented the modules in their classrooms in the subsequent year. Some of the teachers were unable to implement the modules because they did not teach 9th grade physics the following year. Others did not implement the module, since it required substantial amount of classroom time that they preferred to dedicate to topics mandated by the standard 9th grade curriculum. Similarly, Farris et al. (2019)

wrote that “evident in the teacher’s instructional approach was the tension between supporting students’ exploration (of the computational model) and the curricular need for the production of canonically correct representations... that are mandated by the curriculum and that they would need in standardized tests.” We conclude that in order to encourage more teachers to implement such time consuming, challenging learning modules, they should be included national curricula and teacher training programs. In our case, we found that the “free-fall” module, which is more aligned with the middle-school curriculum, has a better chance to be implemented than the oscillations module. Another way that may be useful for streamlining the learning module is by embedding the programming activities in a learning management system such as Moodle. In the workshop, teachers had to split their attention between a paper worksheet, and the VPython code on the computer. In a revised version of the module that was created to support teachers in distance teaching during the COVID-19 shutdown, we embedded the VPython code within an online worksheet in a learning management system. This places the programming section as an integral component of the learning unit, and can encourage students and teachers to use it.

Yet, another way to encourage teachers to implement is by maintaining a professional learning community of the implementing teachers. In a learning community, teachers meet regularly to discuss their successes and challenges in implementation during the school year. This supplements the summer workshop, where teachers experienced most of the learning module as students, and did not have opportunities to rehearse them as teachers. At first, we used a model of individual teacher support that included planning sessions and classroom observations with the PD team. This model of support was only partially successful, since it prevented teachers from sharing stories and reflecting on their implementation challenges with their peers. Promising results from studies of professional learning communities of teachers suggest that they have a better chance to induce changes in teaching and increase teaching self-efficacy (Akerson et al. 2009; Lakshmanan et al. 2011).

Compliance with Ethical Standards Statement

Conflict of Interest The authors declare that they have no conflicts of interest.

Ethical Statement This research was conducted with compliance of the rules mandated by our institution’s Internal Review Board (IRB) and received the approval of the chief scientist of the Ministry of Education in our country.

Consent Statement All of the data sources were consenting adults. All of the subjects in this study were teachers who responded to the surveys by will, and agreed to be video recorded.

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