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# Science educators' views on the role of computational thinking in scientific inquiry

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**Abstract**

Science education in Latin America continues to face persistent challenges, including low student performance and limited teacher preparation in computational thinking (CT). Inquiry-based science education has emerged as a promising framework to enhance student engagement and critical thinking. This cross-sectional study explores Latin-American science educators' conceptions of inquiry-based teaching and learning, CT, modeling, and technological self-efficacy (TSE), and examines how these conceptions relate to their epistemological perspectives. Survey responses from 188 in-service science educators across 12 Latin-American countries were subjected to exploratory factor analysis to derive latent constructs and analyzed using descriptive statistics and k-means clustering to identify the educators' epistemological profiles. The analyses yielded three profiles—traditional, post-Kuhnian, and inquiry-driven—showing distinct patterns across inquiry, modeling and CT conceptions, and TSE. Across the sample and within profiles, higher TSE and more informed conceptions of CT were associated with greater self-reported use of inquiry-oriented approaches. At the same time, misconceptions about CT and limited technological confidence emerged as barriers to integration. These findings suggest that professional development should be differentiated by educator profiles, with an emphasis on strengthening TSE and clarifying the role of CT within inquiry-based science instruction to support more effective classroom integration across Latin America.

**Keywords:** Latin America, inquiry, computational thinking, exploratory factor analysis, k-means clustering, teacher profiles

## INTRODUCTION

Science education in Latin America continues to face significant challenges that contribute to consistently low student learning outcomes. According to PISA results, students in the region lag considerably behind their peers from OECD countries in science and mathematics (OECD, 2019). On average, students from Latin-American countries are approximately three years behind in reading, mathematics and science, and progress in these areas has stagnated over the past two decades. In Colombia, for instance, this performance gap is exacerbated by the inadequate resources available in schools, including a shortage of qualified teaching staff. In PISA, only 7% of Colombian students attained high proficiency levels in science, well below the OECD average; this reveals a deficiency in students' competence to apply scientific knowledge creatively and autonomously across various contexts. Consistently poor results underscore the pressing need for reforms in Latin-American science teacher education programs to address these systemic issues and improve science education outcomes.

While these challenges persist and have a significant impact on the lives of millions of Latin-American children and adolescents, the knowledge and skills required for success in science and mathematics are continually redefined by educational experts. An emerging area of content is computational thinking (CT), which is now regarded as an essential component of


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**Contribution to the literature**

- This study addresses a neglected regional gap by examining how Latin-American science educators' epistemological stances shape the integration of CT within IBSE—an intersection largely explored in the Global North.
- Using exploratory factor analysis (EFA) to derive latent constructs (teaching as modeling [TM], inquiry-based learning, conceptions of CT, technological self-efficacy (TSE), and views of scientific models and methods [SMM]) and then clustering, we have identified three distinct educator profiles.
- Results indicate that higher levels of TSE and clearer conceptions of CT are associated with greater engagement in inquiry- and research-based classroom practices, whereas misconceptions and lower confidence in technology will act as barriers.

"citizen literacy" that all students must acquire *to be able to participate actively in the global society* (Angeli et al., 2016; Espinal et al., 2023; Katai, 2020; Sherwood et al., 2024). CT encompasses key concepts and skills from computer science, such as algorithm design, debugging, pattern recognition, abstraction and decomposition. These skills are increasingly recognized as vital across all disciplines, particularly in science and mathematics, prompting calls from both academia and governments to integrate CT into K-12 curricula. It is recognized that CT practices can enhance learning in subjects such as physics, chemistry and biology, while these scientific disciplines can, in turn, provide rich contexts for students to engage meaningfully with CT concepts and skills (Weintrop et al., 2016). Although these challenges are often documented at the school level (e.g., PISA), science teacher preparation and professional development (PD) in Latin America spans multiple educational levels. Accordingly, this study examines in-service science educators working across preschool, primary, secondary and higher education, recognizing that many CT-related initiatives and teacher training efforts are currently concentrated in higher education and teacher education programs.

Countries from the Global North have made significant progress in integrating CT into their K-12 curricula and in preparing science educators to develop their students' CT skills, but Latin-American countries are still behind in these endeavors (Espinal et al., 2024). Only recent efforts have shown early interventions for PD (Espinal et al., 2024), and for systematic research into how students can learn CT in context (Espinal et al., 2023). However, beyond documenting slower curricular uptake, there is limited cross-national evidence in Latin America on how science educators conceptualize CT in relation to inquiry-based science education (IBSE) (Diordieva et al., 2019), how confident they feel using digital tools to enact CT-oriented inquiry, and whether these beliefs form distinct, recurring patterns. Research in the Global North has begun to map science educators' CT conceptions and implementation challenges, but comparable, multi-country empirical characterizations remain scarce in Latin-American contexts (Belmar, 2022). This limits the ability to design PD that is responsive to heterogeneous starting points among science educators.

There is also a global interest in the development of CT skills from early childhood, and the benefits it could offer to all students by integrating it into science classrooms (Weintrop et al., 2016). However, this integration presents a significant challenge for science educators, as they may not feel prepared to teach CT. Therefore, there is a growing need to prepare science educators and systematically involve them in PD activities that help them learn and restructure their knowledge and attitudes toward CT integration in science teaching. A first step toward achieving this change is to identify science educators' *epistemological* beliefs about inquiry-based teaching and how these beliefs relate to CT, as this characterization can inform the design of interventions for the training and PD of science educators (Ogegbo & Ramnarain, 2022).

The relevance of CT in the professionalization of science educators extends beyond formal conceptual knowledge to its potential to strengthen core epistemic practices of science, particularly scientific inquiry. Although many secondary science educators define CT in basic terms—often as general logical thinking or problem solving—, evidence indicates that some of them hold *informed* intuitions about its role in structuring inquiry, analyzing data, supporting evidence-based decision making, and enabling authentic scientific experiences. This gap between limited formal definitions and more sophisticated functional understandings might point at a recognition by science educators of an alignment between CT and contemporary scientific practices.

From both a theoretical and a practical perspective, CT can be understood not merely as a set of computational skills but as a cognitive and epistemic scaffold that supports IBSE. Recognizing science educators' existing intuitions about CT provides productive foundations for PD, allowing CT to be positioned not as a technological add-on but as a cross-cutting component that coherently and sustainably enhances science teaching and learning (Kite & Park 2023).

Nevertheless, the limited availability of PD opportunities for CT teaching remains a major challenge (Barr et al., 2011; Lee et al., 2011), as science educators often have misconceptions about what CT entails, which impact negatively on how they teach it.

Recent studies have shown that CT may be integrated into science education using inquiry-based education (Sengupta et al., 2013; Sulistiyo & Wijaya, 2020). Among the various meanings of inquiry proposed by Barrow (2006) and the National Research Council (1996, 2000, 2012), we will adopt here one of the interpretations suggested by Barrow (2006), which understands it as a *teaching approach*, or *pedagogy*. IBSE enables students to construct socially shared models based on evidence obtained through inquiry practices, engaging them in activities similar to those performed by scientists (Castillo-Hernández et al., 2022). Additionally, using IBSE helps developing a set of specific skills *for the sound use of evidence to support claims and conclusions* (Adúriz-Bravo, 2020; Gillies & Baffour, 2017), thereby fostering robust epistemic practices in students (Jiménez Aleixandre, 2012; Kelly, 2008) that are in accord with current views on the nature of science (Adúriz-Bravo, 2020).

Brown et al. (2006) identified several benefits that science educators associate with the use of IBSE, including enhanced student motivation, increased engagement, and, in some instances, improvements in science learning outcomes. However, science educators also reported facing challenges when implementing inquiry-based approaches. Contrary to logistical concerns, the primary barrier identified was ascertaining the teacher's role during the inquiry process. Participants in the study believed that inquiry-based instruction should be entirely student-driven, with students taking the lead in posing questions, designing investigations, collecting data, and drawing conclusions; this view represents a significant shift in their traditional ways of teaching.

While IBSE has shown promising results in controlled settings, there is also evidence that, in the complex Latin-American contexts, students exposed to inquiry-based science teaching practices show a lower performance compared to more "direct" ways of instruction (Aditomo & Klieme, 2020; Cairns, 2019; Chaia et al., 2017; Gómez & Suárez, 2020). From such results, it becomes relevant to explore Latin-American science educators' conceptions of inquiry-based teaching and how these relate to their understanding of CT. Specifically, this study explores the following research questions (RQs):

**RQ1:** What latent constructs underlie Latin-American science educators' conceptions of inquiry-based teaching, CT and modeling, and how do these constructs combine into distinct epistemological profiles?

**RQ2:** How is science educators' TSE associated with their conceptions of CT and inquiry-based teaching, overall and within the identified epistemological profiles?

Anticipating the diversity of science educators' conceptions, we also want to explore the different ways in which they understand science education and science teaching. Finally, yet another objective in the study is to correlate science educators' views on CT with their TSE, which is a key element for CT integration. While CT can be partially developed using unplugged approaches (Bell & Vahrenhold, 2018), it is important that students are able to apply these concepts using computational tools (Espinal et al., 2024), so science educators need to feel confident to use such tools.

This article argues that the identification of epistemological profiles in science educators is essential for designing specific PD tracks for CT + IBSE, as available evidence indicates that science educators' conceptions of inquiry, CT, modeling and technology use do not vary independently, but instead cluster coherently according to the distinct epistemological stances underlying educators' discourse. Recognizing science educators' epistemological profiles provides a grounded basis for tailoring PD trajectories, enabling interventions to address differentiated needs, such as strengthening TSE, deepening model-based views of inquiry, or consolidating the epistemic role of scientific thinking in scientific explanation (Amador-Rodríguez et al., 2023a). Hence, the development of epistemological profiles goes beyond a *descriptive* purpose, and functions as a design tool for creating coherent and developmentally informed PD pathways for CT-IBSE integration.

The study follows a sequential analytical strategy in which latent constructs are first identified through EFA and then employed to:

(1) characterize epistemological profiles through clustering, and

(2) examine associations between TSE, CT and inquiry-based teaching practices.

## THEORETICAL FRAMEWORK

### Science Teaching Through Inquiry

We embrace the idea of understanding school science primarily as a "process" (scientific activity) rather than as "product" (scientific results) (Adúriz-Bravo, 2020; Hodson, 2003). From a theoretical perspective grounded in the concept of *evidence*, we propose that engaging in school scientific inquiry involves collecting, structuring and utilizing evidence to comprehend the natural world. We will refer to this process of using evidence to explain as school scientific inquiry (Adúriz-Bravo, 2020), identifying it with "a variety of processes and ways of thinking that support the development of new knowledge in science in school" (Cakir, 2011).

Specialists in science education who have adopted the so-called *semantic view of scientific theories* for school science characterize scientific research as a model-based endeavor (Adúriz-Bravo, 2020). Adherence to this didactical model provides solid and fruitful epistemological foundations for science teaching, which, within this theoretical framework, is portrayed as the organization of problem-solving activities where the central feature is the use of evidence in the construction of school scientific argumentations to explain and control natural phenomena.

School scientific activity intends to describe phenomena in the world around students and requires them to provide reasons to support their claims (Izquierdo-Aymerich & Adúriz-Bravo, 2003). This kind of activity is closely related to major epistemic processes in scientists' science: scientists produce "convincing" results through different methodologies, and those results support specific theoretical interpretations of the world. The inquiry-based approach involves the collection of evidence through the use of models—an activity in which the theoretical models in science guide and even "shape" our observations, explanations, predictions and interventions on phenomena. Modeling, or promoting model use and construction in the science classroom, links to inquiry as follows: scientific models provide structure, coherence and direction to a body of evidence that emerges during the exploration of phenomena (Adúriz-Bravo, 2020; Develaki, 2017; Passmore et al., 2014). Once committed to this theoretical framework, it becomes crucial to consider science educators' conceptions of inquiry and models.

In a famous study, Justi and Gilbert (2003) highlighted the existence of a variety of perspectives on models among practicing science educators. Some science educators perceive a model as a replica of something, while others conceptualize a model as a simplified abstraction. There are science educators asserting that models are subject to modification; others link the concept of model to mental imagery. Within the same group of science educators in the study, a fraction acknowledges multiple applications for models, including the ability to make predictions.

Our conception of inquiry-based science teaching with models involves a series of strategies aiming at supporting student-driven exploration of phenomena. One of these strategies focuses on the formulation of good questions. Students are encouraged to ask questions about the world around them, and the teacher helps them find answers through investigation and exploration (Barkley et al., 2014). A characterizing trait of inquiry-based teaching is its emphasis on hands-on learning experiences, but we want to move beyond this conception and give a central role to the use of theoretical models while intervening on phenomena. By conducting explorations, observations, experiments and simulations, testing real-world situations, and analyzing results through the lens provided by models, students are able to construct their own argumentative understanding of the scientific content that is being taught (Berland & McNeill, 2010).

One of the core tasks undertaken by scientists is to create heavily theoretical explanations of the world in order to successfully intervene on it. This activity is epistemologically understood in the semantic view of science as the formulation, application and adjustment of theoretical models. A model serves the purposes of representing, explaining and facilitating interventions in the world (Izquierdo Aymerich & Adúriz-Bravo, 2021). Inquiry-based teaching can then use scientific models as an instructional tool to support students' learning.

School scientific models serve as elaborate representations that elucidate and predict the behavior of systems and phenomena. Models can assume various forms, such as mathematical equations, computer simulations, diagrams, physical prototypes or mental representations. The primary purpose of a scientific model is to simplify and abstract the crucial aspects of the real-world system while retaining its essential behavior. Although models enable predictions about the real-world system, they are theoretical simplifications of reality, capturing only the fundamental features of the system being modeled. Additionally, a theoretical model can be described as a nonlinguistic entity that embodies the rules established by statements or propositions formulated in a distinct symbolic system (Adúriz-Bravo, 2013; Amador-Rodríguez et al., 2023a).

Yet another important aspect in the model-based inquiry approach adopted here is collaboration and teamwork. Students should be encouraged to work together in small groups, sharing their ideas and insights with one another. Collective modeling is a central feature of science; in the classroom, it fosters a sense of a learning community in the classroom and helps students develop social skills and teamwork abilities (Barkley et al., 2014).

## Computational Thinking and Technological Self-Efficacy

CT comprises a set of socially relevant concepts and skills from computer science (and other disciplines linked to data, information and communication) that are now considered a new form of literacy (Bers, 2020). CT includes valuable operative skills such as algorithm design, debugging, decomposition and abstraction, and various concepts related to hardware and software. Researchers, educators and governmental agencies argue that all students need to develop a minimum of computational and informational skills to actively participate in a data-driven world, very much structured around computers and digital devices (Barr et al., 2011; Furber, 2012; Lee et al., 2011).

In higher education, the skills listed above are not exclusive for engineers or computer scientists; nearly all disciplines today include strong computational approaches to understanding the phenomena they study. In the disciplines, computer-based practices enable people to represent complex phenomena and express ideas. Hence, developing CT skills in only a selected part of the population may further expand globally existing inequalities in education and in the labor market.

As already said in the introduction, integrating CT into the school curriculum may bring about significant challenges. There is no formal pre-service teacher education in CT, and only a few pre-service teacher programs have started to incorporate specific modules or courses (Mouza et al., 2017; Yadav et al., 2017). There is limited infrastructure in schools, particularly in public and rural schools (Vieira et al., 2023). There are also misconceptions about what CT entails, and many science educators still think that this is solely the responsibility of technology educators. However, CT may be better developed across the curriculum, integrated into the different disciplinary courses (Weintrop et al., 2016); this study is particularly interested in the integration of CT in *science* courses. Computational practices indeed support disciplinary learning, and the disciplines, in turn, provide meaningful contexts to develop computational skills and knowledge.

Integrating CT into science courses requires that science educators develop an understanding of how CT helps toward more robust explanations of scientific phenomena, but we also need to ascertain which instructional practices are more effective in using relevant technologies to support student learning. While CT concepts and practices can be first introduced using unplugged approaches, most implementations of CT learning environments end up applying what was learned using technological tools (Espinal et al., 2024), which need not be sophisticated. Thus, science educators must feel comfortable using technologies in the classroom if they are going to integrate CT content. Science educators' self-efficacy beliefs related to technologies are a key contributor to their motivation to satisfactorily perform the professional tasks linked to CT teaching (Boulden et al., 2021).

In general, self-efficacy can be defined as an individual's perceptions about their ability to satisfactorily complete a task and achieve a valid outcome (Bandura, 1990, 2006). Self-efficacy influences motivation and commitment: if I do not believe I am capable of performing a task, I might not be motivated or committed to conduct it. Self-efficacy beliefs hold significance insofar they strongly influence *our intrinsic motivation and our agency* when tackling any relevant activity, including teaching (Bandura, 1990, 2006; Deci & Ryan, 2004; Klemencic, 2015). A person's perception of their efficacy can impact various aspects, including the time dedicated to a task, the effort invested, expectations of the outcome, stress levels, and resilience in the face of challenges. In the context of our research, TSE refers to science educators' perceived ability to use various technologies in their classroom practices.

The previous sections argued in favor of the relevance of inquiry-based teaching and posed the question of how this is conceptualized by science educators. It is stated here that inquiry-based teaching practices may support student learning when they integrate CT concepts and practices to represent scientific phenomena, especially when using computational models (Sengupta et al., 2013; Vieira et al., 2019).

The importance of assessing science educators' TSE in the context of characterizing science educators' understanding of scientific inquiry and CT has also been stated. Science educators' ideas on how to conduct the teaching of their subject matter, particularly in contexts where learning has demonstrated poor results (Gómez & Suárez, 2020), is another variable to be studied.

## Computational Thinking in Science Education

A taxonomy on CT-assisted teaching proposed by Weintrop et al. (2016) appears relevant for understanding the actions performed when promoting activities that integrate CT and school science. In this taxonomy, four major categories are described: data practices, modeling and simulation practices, computational problem-solving practices, and systems-thinking practices. Each of these categories, in turn, is composed of a subset of other specific practices. Weintrop et al. (2016) assert not only the close links between CT and school scientific practices, but also how computational technology is transforming the very nature of those practices. The use of CT has recently been included as one of the eight key "scientific practices" in STEM approaches (Bybee, 2011).

We posit that the processes of modeling and inquiry promoted in schools within the theoretical framework to which we adhere—i.e., the expression, discussion and iterative revision of the models that students build (Adúriz-Bravo, 2013; Justi & Gilbert, 2003)—entail highly exploitable, progressive educational practices to experiment and develop computational activity related to computer modeling. The conceptual proposal by Weintrop et al. (2016) enables us to support the idea of connecting CT to inquiry. This bibliographical reference provides concepts and notions that will help us consider the varied perspectives that Latin-American science educators hold regarding inquiry, CT, and their interconnections.

### Epistemological Periodization as Analytical Tool for Teacher/Educator Profiles

In this study, a specific periodization of the philosophy of science in the 20th century provides a structured way of understanding the evolution of scientific thought and how it has been conceptualized by the different philosophical schools. We find this map of reconstructions of the *nature of science* relevant for science educators and researchers in the field of science education (Amador-Rodríguez et al., 2023a, 2023b). In particular, it can be used as analytical tool to understand epistemological positionings in science education.

The periodization used here to understand science educators' "epistemologies" comprises three distinct periods:

1. *Knowledge through conjectures and refutations:* During this first period—epistemically embodied by Austrian-British philosopher Sir Karl Popper—, the philosophy of science sought to challenge the theoretical foundations of early 20th century logical positivism. Within critical rationalism, scientific progress is understood as a recurring process in which theories are falsified and rejected, then replaced by new theories that offer greater explanatory and predictive adequacy.
2. *Theory-leadenness of observation:* The perspective of this second period challenges the assumed neutrality and objectivity of science. It acknowledges that scientific concepts carry a theoretical "load," and that every observation is influenced by the underlying theory used to perceive the world. It also refutes the existence of the renowned scientific method.
3. *Recent, model-based accounts of the nature of science:* This last period comprises a manifold of epistemological schools. One of these, already mentioned above, is the semantic view of scientific theories, focusing on the meaning and use of scientific theories. Many contemporary philosophers of science postulate that the relationship between phenomena and what science says about them is mediated by scientific models as abstract representations of the world.

The epistemological periodization presented above builds on others previously employed to characterize science educators' epistemological profiles (Amador-Rodríguez et al., 2023a, 2023b; Badillo et al., 2024). The new, simplified version used in this study includes three epistemological positionings that offer a refined approach towards depicting science educators' ideas on some key aspects of the nature of the scientific activity, particularly in relation to inquiry.

### From Theoretical Perspectives to Measurable Constructs

In **Table 1**, we present the representations of the epistemic aspects from the epistemological periodization introduced above, which makes it possible to understand inquiry-based teaching and CT.

**Table 1.** Epistemic aspects represented in IBSE and CT

| Constructs | Epistemic aspects represented | |
|---|---|---|
| | For IBSE | For CT |
| TM | Inquiry-based science teaching becomes more meaningful when it is framed as inquiry for modeling: the goal is to construct, use, evaluate and revise models to explain phenomena, thereby making explicit key epistemic aspects of science (what counts as evidence, how explanations are justified, and when a model should be revised), so students learn scientific content as well as how scientific knowledge is produced and validated (Couso, 2014). | Science TM treats the classroom as a space where students learn science by building and revising computational simulations that make their explanations explicit. Through iterative design, peer critique and comparison with measurements, students develop disciplined interpretation: they link programming choices (variables, rules, loops, assumptions, visual encodings) to scientific meaning, recognize data as constructed and error-prone, and refine models using emerging criteria for what counts as a "good" representation (Farris et al., 2016). |
| IL | Integrating inquiry into learning entails that students learn science by engaging in inquiry practices (asking questions, analyzing data, constructing explanations). When teaching includes this epistemic dimension, it highlights criteria for warranting knowledge and uses scaffolds (Sandoval & Reiser, 2004) to improve the quality of explanations and to understand science as justified and revisable knowledge. | In scientific inquiry, learning science involves asking questions, building explanations, and revising them with evidence. From a teaching perspective, CT strengthens inquiry when instruction is designed around model-based investigations (e.g., emergent systems microworlds) and the teacher scaffolds the sequential use of practices—questioning, using models, planning investigations, analyzing data, and constructing explanations— in alignment with key disciplinary ideas. This kind of scaffolding supports epistemic connections between practices and core concepts, tightening the link between mechanisms, evidence and explanation (Dabholkar et al., 2020). |

**Table 1 (Continued).**

| Constructs | Epistemic aspects represented | |
|---|---|---|
| | For IBSE | For CT |
| CTC | Representing epistemic aspects means making it visible in classroom activity what counts as evidence and how conclusions are justified and revised. Depending on how CT is conceived, inquiry can be organized as a propose-test-refine process that foregrounds epistemic criteria for validation. In Tsakeni (2021), CT supports preservice science educators in planning and sustaining inquiry-based practical work in constrained contexts through step-by-step planning, evaluation, and iteration aimed at producing more reliable classroom knowledge. | Sengupta et al. (2018) argue that CT is not merely a set of procedures but a practice in which people construct knowledge by interacting with models, rules, and computational outputs. This interaction makes explicit assumptions about how knowledge is produced (exploring, testing hypotheses, iterating models) and how it is justified (model coherence, explanatory/predictive value, patterns and simulation outputs as evidence). Thus, programming/modeling is a means to develop and refine explanations, not an end in itself. |
| TSE | In virtual inquiry, the teacher is crucial for equitable access to practices. Ketelhut (2007) shows that students' entry self-efficacy is linked to greater initial evidence-gathering, although these differences tend to diminish over repeated visits. Therefore, instruction should scaffold both tool use and epistemic criteria (where to look, how to judge data quality, how to connect evidence to claims) so the technology supports—rather than distracts from—students' scientific reasoning. | In computing, the teacher can strengthen students' self-efficacy by designing lessons around inquiry and engineering design, not mere device use. Following Psycharis et al. (2021), the teacher structures physical computing tasks as an iterative cycle—question → test with observable evidence (e.g., sensor data) → interpret → debug → redesign/optimize— and uses real-life scenarios to avoid decontextualized programming. By normalizing debugging and requiring justification of design choices, the teacher turns programming into modeling and verification, conditions linked to significant gains in CT self-efficacy. |
| SMM | From this perspective, models are not final products but epistemic tools for explaining phenomena, generating predictions, guiding evidence seeking, and subjecting explanations to empirical scrutiny. Scientific methods (observation, measurement, experimentation, data analysis and argumentation) produce evidence and assess the strength of model-based claims. Kelly (2014) argues that explicitly integrating models and methods into school inquiry makes visible not only what is known, but how it becomes known and why it is considered valid within a scientific community. | When programming a model, students must decide which entities, variables, and relationships to include (what counts as relevant in the phenomenon). By running simulations, they adopt a method for testing and validation by comparing outputs, patterns and inconsistencies. Iteration—revising assumptions and rules and re-simulating—mirrors a key scientific methodology; particular forms of participation ("epistemic gameplay") support stronger explanations. Thus, in model-based inquiry, CT does not merely support science; it embodies the epistemic processes of scientific modeling and methods (Wilkerson et al., 2018). |

## MATERIALS AND METHODS

This study uses an exploratory design to understand Latin-American science educators' conceptions of inquiry-based teaching, CT, and their relations. We carried out a survey with statements concerning several aspects of inquiry-based teaching, CT, modeling and TSE to characterize science educators' conceptions on those issues. The participants were asked to indicate their agreement or disagreement with each of the 44 statements on the instrument. Responses on a 5-point Likert scale ranged from 1 to 5 (where 1 = strongly disagree, 3 = neutral/uncertain, and 5 = strongly agree).

### Participants

Participants were recruited through the REDLAD academic and professional network, and through its members' dissemination channels. The study this used a non-probabilistic convenience sample based on voluntary participation. As a result, the sample may be affected by self-selection bias, potentially over-representing science educators who are more interested in inquiry-based teaching, CT or professional networks, and may under-represent science educators with limited access to such networks or lower technological confidence. Additionally, the recruitment channels may have led to a higher proportion of participants linked to higher education and/or with advanced degrees, which may limit the representativeness of science educators working exclusively in primary/secondary settings.

A total of 188 science educators participated in the study (94 from Colombia and 94 from other Latin-American countries; see **Table 2**). We emailed an invitation to science educators across all South American countries (excluding Suriname and Guyana), as well as

**Table 2.** Country of origin of participant science educators

| Country of origin | Number of science educators |
|---|---|
| Argentina | 18 |
| Brazil | 3 |
| Chile | 20 |
| Colombia | 94 |
| Costa Rica | 3 |
| Cuba | 1 |
| Ecuador | 2 |
| Italy* | 1 |
| Mexico | 40 |
| Panama | 1 |
| Peru | 1 |
| Venezuela | 4 |
| Total | 188 |

* Although one response is recorded as having a location in Italy, it corresponds to a Latin-American participant who, at the time of completing the survey, was temporarily residing in that country (since the study's inclusion criterion was based on the participant's identity/professional experience linked to the Latin-American context (rather than their momentary geographic location when responding), this case was retained in the analysis)

**Table 3.** Educational level where participants teach

| School level | Number of science educators |
|---|---|
| Preschool | 8 |
| Elementary school | 24 |
| Secondary school | 49 |
| Higher education | 106 |
| Non-formal education | 1 |
| Total | 188 |

to selected countries in the Americas and Europe. Those are the countries of origin of the science educators and researchers affiliated with REDLAD, a continental association for science education research.

The invitation was open to educators at all educational levels (see **Table 3**) and included a link to an online survey. Participants reported teaching at multiple educational levels, with most working in higher education (n = 106).

Inclusion criteria comprised in-service science educators currently teaching science-related subjects at any educational level. A small number of respondents reported teaching in areas such as social sciences or technology; these cases were retained in the sample because their responses referred to science-related instructional practices and did not present missing data in the analytical constructs. No responses were excluded from the dataset prior to analysis, except for cases with incomplete data on the specific variables required for each statistical procedure.

**Table 5.** Demographic information of the respondent science educators: Education

| Degree | BSc | MSc | PhD | NA |
|---|---|---|---|---|
| n | 23 | 83 | 55 | 27 |

Note. The highest degree of the science educators is shown (N = 188)

**Table 6.** Demographic information of the respondent science educators: Teaching experience

| Experience | 0-1 | 1-2 | 2-3 | 3-4 | 4-5 | 5+ |
|---|---|---|---|---|---|---|
| n | 13 | 43 | 31 | 17 | 17 | 67 |

Note. Number of science educators per range of years of teaching experience is shown (N = 188)

Demographic information of the participating science educators is presented in **Table 4**, **Table 5**, and **Table 6**. We had 90 female and 98 male science educators. More than 70% of the participants had completed a graduate program, and nearly 35% (67 science educators) had five or more years of teaching experience. Most science educators taught science; 14 of them taught either social sciences or technology.

### Instrument Development and Adaptation

The survey consisted of 44 Likert-type items compiled from multiple published instruments addressing inquiry-based teaching (Barkley et al., 2014), CT (Weintrop et al., 2016), modeling (Justi & Gilbert, 2003), epistemological views (Amador-Rodríguez et al., 2023b), and TSE (Klemencic, 2015). Because the original items were developed in a variety of languages, we implemented an adaptation procedure to ensure semantic and contextual equivalence for Latin-American educators. First, items were translated and adapted by bilingual researchers, followed by back-translation. Next, wording was adjusted to match national curriculum terminology and local teaching practices. All changes aimed at preserving the original construct meaning while ensuring clarity and relevance for the target context.

## DATA COLLECTION AND ANALYSIS

### General Approach

We administered an online survey to participating in science educators to elicit their teaching conceptions; the complete set of items is presented in **Appendix A**. The instrument drew on items from several published sources, including Barkley et al. (2014), Weintrop et al. (2016), Justi and Gilbert (2003), Amador-Rodríguez et al. (2021), and Klemencic (2015), which also document

**Table 4.** Demographic information of the respondent science educators: Teaching subjects

| Subject | Biology | Chemistry | Physics | Other natural sciences | Math | All areas | Social sciences | Technology | NA |
|---|---|---|---|---|---|---|---|---|---|
| n | 30 | 36 | 18 | 57 | 9 | 11 | 12 | 2 | 13 |

Note. Number of science educators per teaching subject is shown (N = 188)

**Table 7.** KMO coefficient for each item

| Item | Q1 | Q2 | Q3 | Q5 | Q6 | Q7 | Q9 | Q10 | Q11 | Q12 | Q14 | Q15 | Q16 | Q17 | Q18 | Q19 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Coefficient | 0.82 | 0.73 | 0.83 | 0.83 | 0.60 | 0.77 | 0.67 | 0.72 | 0.81 | 0.82 | 0.83 | 0.79 | 0.82 | 0.52 | 0.77 | 0.71 |
| Item | Q20 | Q21 | Q22 | Q23 | Q24 | Q25 | Q26 | Q27 | Q28 | Q32 | Q33 | Q38 | Q39 | Q40 | Q41 | Q44 |
| Coefficient | 0.80 | 0.68 | 0.81 | 0.72 | 0.84 | 0.74 | 0.74 | 0.75 | 0.60 | 0.61 | 0.74 | 0.73 | 0.71 | 0.73 | 0.79 | 0.71 |

**Table 8.** Factor loadings and eigenvalues for the five latent constructs

| Item | Factor 1 | Factor 2 | Factor 3 | Factor 4 | Factor 5 |
|---|---|---|---|---|---|
| Q14 | 0.85 | | | | |
| Q11 | 0.79 | | | | |
| Q5 | 0.73 | | | | |
| Q15 | 0.67 | | | | |
| Q1 | 0.66 | | | | |
| Q3 | 0.66 | | | | |
| Q12 | 0.66 | | | | |
| Q18 | 0.65 | | | | |
| Q2 | 0.64 | | | | |
| Q7 | 0.55 | | | | |
| Q6 | 0.41 | | | | |
| Q22 | | 0.84 | | | |
| Q25 | | 0.78 | | | |
| Q19 | | 0.76 | | | |
| Q21 | | 0.74 | | | |
| Q24 | | 0.71 | | | |
| Q20 | | 0.69 | | | |
| Q23 | | 0.68 | | | |
| Q27 | | 0.65 | | | |
| Q26 | | 0.55 | | | |
| Q41 | | | 0.79 | | |
| Q40 | | | 0.73 | | |
| Q44 | | | 0.67 | | |
| Q38 | | | 0.65 | | |
| Q39 | | | 0.59 | | |
| Q10 | | | | 0.74 | |
| Q9 | | | | 0.69 | |
| Q16 | | | | 0.59 | |
| Q17 | | | | 0.47 | |
| Q32 | | | | | 0.83 |
| Q33 | | | | | 0.66 |
| Q28 | | | | | 0.65 |
| | MR1 | MR2 | MR3 | MR4 | MR5 |
| E | 5.57 | 4.94 | 2.94 | 2.40 | 2.05 |
| PCV (%) | 0.17 | 0.33 | 0.42 | 0.50 | 0.56 |

Note. E: Eigenvalues; PCV: Percentage of cumulative variance

adaptation procedures for the Latin-American context. In addition, two members of the research team met three times over a two-week period to identify the most relevant items and the constructs expected to emerge. The CT and TSE items had also been previously used and locally validated in a nationwide PD program. To examine the latent structure of the data, we conducted an EFA. Sampling adequacy was assessed using the Kaiser-Meyer-Olkin (KMO) index based on the polychromic correlation matrix, and items with KMO values below 0.50 were removed sequentially. The overall KMO was 0.75, indicating meritorious sampling adequacy, and Bartlett's test of sphericity was significant, $\chi^2(496) = 4,041.064$, $p < .001$, confirming that the correlation matrix was appropriate for factor analysis. **Table 7** reports the KMO coefficients for the items retained in the analysis.

We then selected the number of factors by considering an eigenvalue larger than 1 and used a cutoff value of 0.4 for the factor loadings. We used the Varimax rotation method as the underlying constructs showed small correlations, and the minimum residual method given the limited sample size (N = 188). The factor loadings and eigenvalues are presented in **Table 8**, while **Table 8** with all factor loadings is presented as **Appendix B**.

This method confirms the five constructs identified in this study, as follows:

1. TM: This construct refers to elements related to model-based instruction proposed by science educators in their teaching; it includes the relation of models and inquiry. Examples of items for this construct are: "In my classes, I teach that science advances because scientists choose the best scientific model, the one most similar to the phenomenon being studied" and "In my classes, I teach that scientists create laws, hypotheses, models or theories to describe what happens in nature."
2. Inquiry in learning (IL): This construct assesses the extent to which science educators think that the implementation of hands-on teaching activities engages students in the development of scientific inquiry for science learning. Two sample items measuring this construct include: "In my classes, I encourage students to spend time in the lab doing hands-on experiments" and "In my classes I promote that students have the opportunity to explain their ideas."
3. Computational thinking conceptions (CTC): This construct assesses whether science educators identify relevant learning outcomes associated with CT practices and concepts. The main item for this construct asked science educators to assess to what degree each of a list of elements represented learning outcomes for computational topics, for example: "create and use models and simulations" and "automate tasks."
4. TSE: This construct reflects science educators' beliefs related to their ability to use digital technologies in the classroom, e.g., "I can easily learn about new technologies", "I know how to

use ICTs with students in class" and "I know how to solve technical problems when ICT fails."

5. SMM: This construct evaluates the views on models and modeling that science educators introduce in their inquiry-based teaching practices. Two sample items are: "In the scientific activity, the relationship between a scientific model and experimental designs is subject to the decisions that scientists make during their research" and "In my classes, I teach that scientists propose scientific models, which are similar to reality because they represent, explain and predict phenomena."

To measure the internal consistency of each construct, we used both Cronbach's alpha and McDonald's omega and found that all constructs are within recommended thresholds. Taber (2018) showed that there are several ranges and threshold values often considered as adequate in the literature of science education. While a higher alpha usually means better internal consistency, these values are often affected by the number of items in the scale and the construct that is being measured.

We computed the following values of Cronbach's alpha and McDonald's omega: TM (alpha: 0.88, omega: 0.9), IL (alpha: 0.87, omega: 0,89), CTC (alpha: 0.78, omega: 0.8), TSE (alpha: 0.75, omega: 0.77), and SMM (alpha: 0.66, omega: 0.69).

## Construction of Evidence

We used descriptive statistics, including the measures of central tendency and variability, in order to explore and describe the participant science educators' conceptions and beliefs about inquiry teaching and learning, CT, scientific models, and their TSE. In addition, we standardized the scores for all constructs, and used k-means, a clustering algorithm, to identify the different groups of science educators based on their beliefs and conceptions. k-means uses Euclidian distance to compare all the points in a data set to a set of random centroids, which are iteratively refined based on these distances. This permitted avoiding hiding different groups under a generalization of central tendencies (Vieira et al., 2018a) and allowed us to describe how science educators differ along these five dimensions. While the elbow and silhouette methods suggested two groups, we selected three groups after exploring the resulting clusters because they were theoretically sound (Vieira et al., 2024). While the 2-cluster solution had the highest silhouette width (0.27), the silhouette values for all solutions (K = 3, 0.18; K = 4, 0.18) were low overall, suggesting weakly separated cluster structure. Under these conditions, interpretability and theoretical coherence become particularly important in selecting among candidate solutions. The 2-cluster solution appeared to capture the broadest division in the data, whereas the 3-cluster solution further separated one of these broad groups into two substantively distinct subgroups. Although this reduced overall compactness/separation, it yielded a more nuanced classification that better reflected the underlying theoretical model. However, the bootstrap results indicated that only two of the three clusters showed stability (Jaccard similarities were 0.76, 0.43, and 0.62), whereas the other cluster was unstable. Accordingly, the 3-cluster solution should be interpreted primarily as an exploratory, theory-informed partition.

The analytical procedure was explicitly aligned with the RQs. **RQ1** was addressed by identifying latent constructs related to inquiry-based teaching, CT, modeling and epistemological views through EFA, and subsequently examining how these constructs cluster into distinct epistemological profiles. **RQ2** was addressed by analyzing associations between the TSE construct and science educators' conceptions of CT and inquiry-based practices, both across the full sample and within the identified epistemological profiles.

As the goal of this study was to explore a distribution of science educators' conceptions of inquiry, CT, modeling and TSE, we have not attempted to make inferential comparisons between or within groups. We use descriptive statistics to present measures of central tendency and variability, and then we conduct cluster analysis to identify different teacher profiles. Conducting inferential statistics between these profiles would seem to provide the obvious results: since we group them based on how different they are on these five constructs, the differences would be statistically significant. Instead, we suggest that the interpretation of these three profiles would be a more important contribution of this study.

Missing data were limited to demographic variables (e.g., teaching subject, highest degree, and years of experience) and were explicitly reported as "NA" in **Table 4**, **Table 5**, and **Table 6**. For the main analytical procedures (EFA, clustering, and correlational analyses), only cases with complete responses on the relevant survey items were included. Given the exploratory nature of the study and the low proportion of missing responses, no data imputation procedures were applied, and analyses relied on listwise deletion at the construct level.

Importantly, the survey instrument was not designed to diagnose participants' philosophical positions regarding the nature of science. Therefore, references to philosophical traditions (e.g., Popperian, Kuhnian, or semantic views of science) are used strictly as *interpretive frameworks* to contextualize patterns observed in the data. The cluster analysis identifies empirical profiles based on survey constructs (inquiry, CTC, modeling and TSE), and philosophical interpretations are employed

**Table 9.** Descriptive statistics for each construct

| Constructs | Overall | | Male (N = 95) | | Female (N = 90) | |
|---|---|---|---|---|---|---|
| | Mean | Standard deviation | Mean | Standard deviation | Mean | Standard deviation |
| TM | 74.61 | 18.81 | 78.7 | 13.8 | 70.7 | 21.9 |
| IL | 81.21 | 14.71 | 81.1 | 12.6 | 81.1 | 16.8 |
| CTC | 81.75 | 14.83 | 80.3 | 15.0 | 83.3 | 14.6 |
| TSE | 81.06 | 15.15 | 81.9 | 14.0 | 80.1 | 16.4 |
| SMM | 72.14 | 18.70 | 70.2 | 17.8 | 73.8 | 19.4 |

Note. A total of 188 science educators completed the survey; however, some demographic variables contained missing responses (for example, three participants did not report their gender, so analyses disaggregated by gender were conducted with a reduced sample (N = 185) & minor variations in sample size across analyses are therefore attributable to missing responses in specific demographic variables, and all reported statistics are based on the maximum number of valid cases available for each variable or construct)

**Table 10.** Epistemological profiles of science educators

| Group | TM | IL | CTC | TSE | SMM | Inferred epistemic orientation |
|---|---|---|---|---|---|---|
| 1. Science educators with a traditional conception of teaching | 57.40 | 74.30 | 70.12 | 67.94 | 67.42 | Knowledge through conjectures and refutations |
| 2. Science educators with a logical-empiricist view on models | 78.89 | 82.93 | 83.88 | 86.47 | 49.22 | Theory-leadenness of observation |
| 3. Science educators teaching through inquiry | 84.33 | 85.10 | 88.62 | 87.59 | 84.72 | Recent, model-based accounts of the nature of science |

Note. A total of 188 science educators completed the survey; however, some demographic variables contained missing responses (for example, three participants did not report their gender, so analyses disaggregated by gender were conducted with a reduced sample (N = 185) & minor variations in sample size across analyses are therefore attributable to missing responses in specific demographic variables, and all reported statistics are based on the maximum number of valid cases available for each variable or construct)

cautiously to help situate these profiles within broader theoretical discussions in science education.

## RESULTS

### Constructs Underlying Inquiry, Computational Thinking and Epistemological Views (RQ1)

We first computed the measures of central tendency and variability for each of the constructs using the complete sample. These constructs were computed as a weighted average using the factor loadings for each item. Eq. (1) shows the formula we used for this process:

$$P = \left(\frac{\sum pf_i - \sum f_i}{4\sum f_i}\right) \times 100, \quad (1)$$

where $P$ corresponds to the construct score, $p$ corresponds to each individual item score, and each f corresponds to the factor loading.

These values were then normalized on a scale from 0-100, with the following ranges for interpretation: 0-30: low; 31-70: medium; and 71-100: high. While these ranges seem arbitrary, similar values have been commonly used in existing literature (e.g., Vieira et al., 2018b) and guide the interpretation of results. Overall, the average scores for all constructs are in the highest range, with IL, CTC, and TSE as the highest ranked (**Table 9**).

## DISCUSSION

### Epistemological Profiles of Science Educators and Variation in CT + IBSE Conceptions (RQ1)

Since we did not expect all participant science educators to be within the same ranges for all the constructs, we decided to use k-means as a clustering algorithm to find potentially different groups, or teacher profiles, among the participants.

**Table 10** shows the average value for each of the five constructs in the three groups we identified.

Science educators in group 1 adhere to what we call a "traditional" conception of teaching. This group has the lowest score in TM, and a lower average score for all the constructs (except SMM) compared to the other two groups. Their average scores in TSE and SMM are medium.

These patterns may be broadly interpreted as consistent with more traditional views of scientific knowledge, where science is often presented as a structured and method-driven process. From a philosophy-of-science perspective, such orientations have sometimes been associated with accounts emphasizing hypothetico-deductive reasoning. However, the present study does not measure philosophical positions directly; therefore, these references are used only as interpretive analogies.

Science educators in group 2 have high scores in the constructs TM, IL, CTC, and TSE. The patterns observed in group 2 suggest an orientation that recognizes the interpretive and theory-laden nature of scientific knowledge. In philosophy-of-science discussions, similar perspectives have been associated with post-positivist accounts of science (e.g., Kuhnian and post-Kuhnian traditions). In this study, however, these philosophical perspectives are used only as conceptual lenses to interpret possible epistemic tendencies.

Kuhn's epistemological perspective challenges the traditional idea that scientific observations are objective and neutral, asserting instead that they are always influenced by the observer's perspective and the context. Form this, it follows that observational terms do not provide meaning to theoretical concepts, but rather, the latter determine the former. Furthermore, post-Kuhnian philosophers of science proclaimed the non-existence of the famous "scientific method;" their perspective rejects the idea of a single, universal and validated way of doing science (Feyerabend, 1975). On the contrary, they argue that scientific research is shaped by the Weltanschauungen of the communities of practitioners conducting it, and that different scientific disciplines may require different methods and approaches.

Science educators in group 3 are labeled "inquiry science educators." The orientation of this group—characterized by high scores in modeling, IL, and CTC—can be interpreted as broadly aligned with contemporary views of science education that emphasize modeling as a central epistemic practice. Some philosophy-of-science accounts, such as the semantic view of theories, highlight the role of models as mediators between theory and phenomena. These perspectives provide a useful interpretive framework for discussing the results, but they should not be understood as direct classifications of teachers' philosophical positions.

With these philosophical foundations, science is best taught by helping students construct knowledge through collective and critical use of models. A model-based science teaching that draws upon a semanticist conception of models suggests the crucial need of:

(1) helping students make theoretical interpretations of the world,

(2) providing them with authentic experiences of intervention on phenomena,

(3) encouraging discussion and cooperative learning, and

(4) diagnosing students' previous knowledge (even misconceptions) on the phenomena under study so that bridges toward school science can be constructed.

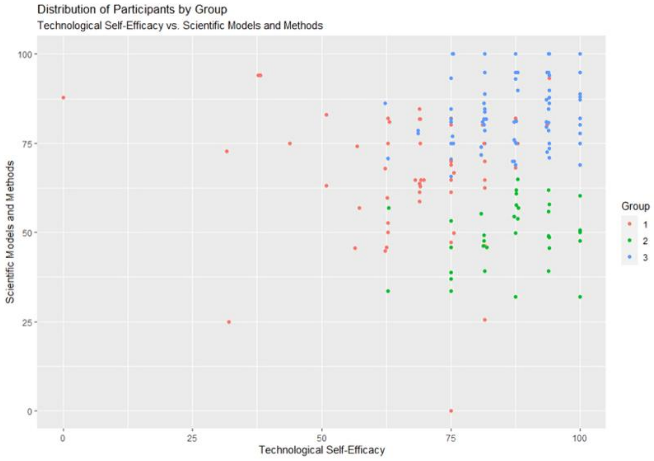


**Figure 1.** Distribution of the three groups of science educators along the dimensions of TSE and SMM (Figure created by the authors)

## Technological Self-Efficacy and Its Association with CT and Inquiry Practices (RQ2)

**Figure 1** represents the distribution of the three groups of science educators along two dimensions: TSE (x-axis) and SMM (y-axis). Higher values in the x-axis indicate greater self-reported efficacy in using technological tools and applications, while higher values in the y-axis represent higher understanding of, and ability to, use of scientific principles and methods.

Group 1 (red points) is the only one having science educators in the lower ranges of both dimensions. This group has generally lower TSE and low to intermediate understanding of SMM. Group 2 (green points) is located in low and mid values on the modeling axis, indicating weaker skills in this dimension. Group 3 (blue points) is primarily located in the upper range of both dimensions, suggesting high self-efficacy in technology use and a strong grasp of scientific principles.

There seems to be a positive correlation between TSE and SMM across all groups. Science educators with higher technological skills also tend to perform better in scientific methods, and this is especially visible in group 3.

As for clustering, the three groups are relatively distinct, with minimal overlap. This suggests clear stratification among science educators based on their competencies in these two dimensions selected for analysis. Only a few data points can be considered as outliers falling outside their main clusters, and this indicates very low variability in the group categories that we constructed.

Science educators like those in group 1 may benefit from targeted interventions focusing on both scientific and technological training. Science educators in the style of group 2 would be those with "unstable" competencies, possibly moving from the profile of group 1 to the profile of group 3. Science educators who, in the future, will eventually be located in group 3 could be

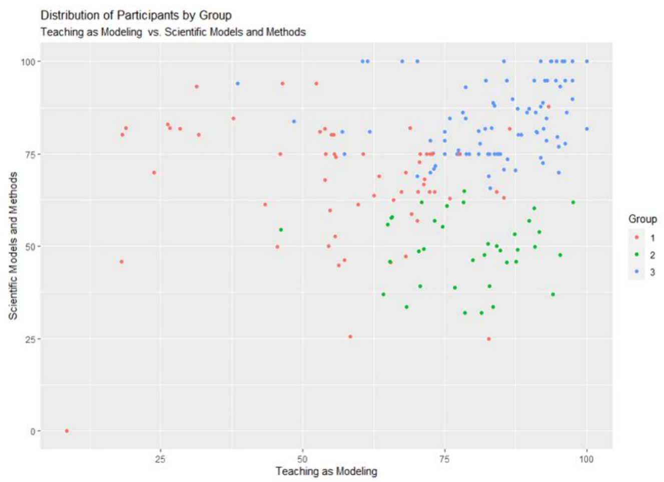


**Figure 2.** Distribution of the three groups of science educators along the dimensions of TM and SMM (Figure created by the authors)

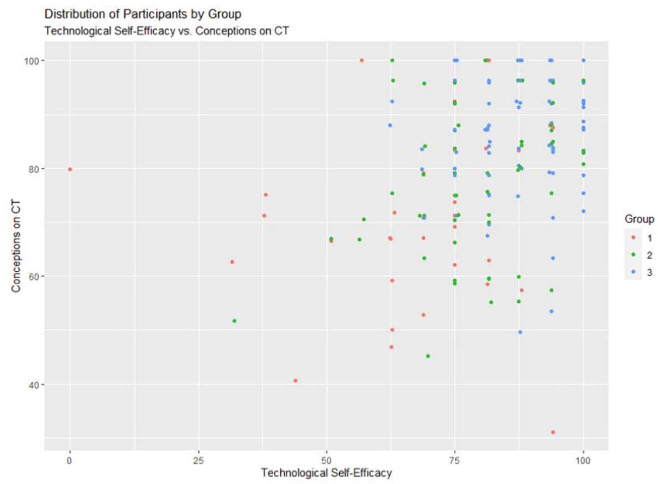


**Figure 3.** Distribution of the three groups of science educators along the dimensions of TSE and CCT (Figure created by the authors)

considered role models for sound, innovative technological and scientific teaching practices, and they could potentially serve as mentors or leaders in PD programs.

Clear-cut clustering can also be found if we correlate science educators' conceptions of TM and of the nature of model-based science (**Figure 2**). Science educators from group 1 (who had both low and high scores in SMM) are now evenly distributed in the TM axis; they represent a rather traditional conception of science teaching. The majority of science educators in group 2 (where we see post-Kuhnian philosophical underpinnings) and in group 3 (committed to inquiry practices) are confident on the educational value of TM, but they differ in the theoretical views on models and modeling that should be introduced in their inquiry-based teaching practices (and this includes the extent of the use of technologies).

Finally, when we map the participants' TSE against their conceptions on CT (**Figure 3**), we identify moderate correlation between these two constructs ($r = 0.37$), which suggests that science educators with a low TSE also have poorer conceptions of what CT entails. Group 1 and group 2 are the ones located at the lower ends of these two constructs, while science educators group 3 seem to have higher TSE and a clearer conception of the role of CT in science education.

## Epistemological Profiles and Their Conceptions of IBSE and CT

Latin-American science educators' conceptions on inquiry-based teaching and CT seem to be varying in accordance with the epistemological beliefs that we have inferred from the analysis. The three epistemological profiles used in our cluster analysis—knowledge through conjectures and refutations for group 1, theory-leadenness of observation for group 2, and recent, model-abed accounts of the nature of science for group 3—"accompany" variations in how science educators engage in innovative science teaching practices.

The science educators in group 1 (with lower scores in IL and CTC, and an inferred *syntactic* approach to school scientific theories) seem to be more likely to adhere to a traditional, structured teaching paradigm, prioritizing content delivery over exploratory or computational approaches. They might feel less comfortable with student-centered inquiry. The science educators in group 2 (with higher scores in IL and CTC, a renewed view on scientific methods, and yet, a traditional approach to models) seem to align with evidence-based, strongly computational teaching practices. But their lower score in SMM could hinder how they execute inquiry in their classrooms. Group 3 (with the highest scores in IL and CTC and probably adhering to a more interesting conception of models such as that from the philosophy of science of the 1980s-1990s) are more likely to consider inquiry and CT as integral components of good teaching, showing more advanced understanding of these two concepts in science education.

## Implications for Professional Development

The identification of three teacher profiles suggests that PD initiatives aimed at integrating CT into IBSE should be differentiated rather than uniform. Instead of generic training programs, PD should address the specific needs, strengths and limitations associated with each profile. In this section, we outline concrete PD design implications for each profile, including learning objectives, design features, example training modules, indicators of success, and potential implementation risks.

### *Professional development for group 1: Traditional-oriented educators*

**Learning objectives:** PD for this profile should aim to

(1) strengthen science educators' TSE,

(2) clarify the role of CT in scientific inquiry, and

(3) gradually shift instructional practices from teacher-centered explanations toward guided inquiry and model-based reasoning.

**Design features:** Effective PD for this group should emphasize structured and scaffolded learning experiences. Training should begin with concrete classroom examples that demonstrate how CT practices (e.g., data analysis, algorithmic reasoning, or simulation) support the explanation of scientific phenomena rather than replacing disciplinary knowledge.

#### *Professional development for group 2: Transitional educators*

**Learning objectives:** PD initiatives for this group should focus on strengthening the integration of scientific modeling with inquiry-based practices and CT.

**Design features:** Training should build on teachers' existing strengths in inquiry practices and their TSE, while helping them conceptualize models as epistemic tools rather than static representations.

#### *Professional development for group 3: Inquiry-driven educators*

**Learning objectives:** For educators already demonstrating strong inquiry and CT orientations, PD should focus on leadership, curriculum design, and mentoring roles.

**Design features:** Training should promote collaborative learning communities where these educators can develop and share innovative instructional practices.

### Implications for the Classroom

Science educators in group 1 could be characterized as those who think that the most effective science teaching method is "imparting" theories as scientific achievements and explaining their structure and validity (this finding aligns with the work of Oh & Oh, 2011). In traditional teaching, presenting models can enhance student learning by making complex scientific concepts more accessible, but the teacher-centered nature of this approach often overlooks the evolving nature of scientific models and the complexities of the modeling process. To address this limitation, the use of models in science classrooms should transcend the traditional focus on transmitting as teaching content a set of established scientific models in their final form. Researchers in science education, as explained above, have emphasized the relationships between science educators' perceptions of models and their instructional practices, highlighting the need for more interactive, student-centered approaches that delve into modeling as a process.

Key characteristics of science educators in group 1:

1. They place less emphasis on TM and IL compared to other groups, suggesting a preference for teacher-centered, *didactic* methods.
2. Their relatively low scores in TSE and SMM imply that these science educators might face challenges integrating technology and scientific methodologies into their teaching practices.

We have connected their approach with some elements of the nature of science that give primacy to the Popperian method of conjectures and refutations, which puts emphasis on structured frameworks, rules and logic over flexible, inquiry-based learning. This aligns with findings reported by Liang et al. (2009); science educators often lack awareness that observations and inferences in science are influenced by theoretical perspectives. Many actors in the science classroom hold the misconception that scientists, due to their objectivity, always make identical observations and interpretations of the same phenomena. However, a group of science educators participating in this study appeared less influenced by the pervasive misconception of the scientific method, which is many times enforced by science textbooks and laboratory manuals. These science educators demonstrated a greater ability to articulate valid examples of various scientific methods in their own words.

Key characteristics of science educators in group 2:

1. They demonstrate strong performance in all areas except SMM, where they score significantly lower.
2. They seem to at least partly apply in their teaching the idea of theory-leadenness of observation, since they adhere to emphasizing logic, evidence and data-driven teaching practices. They still may struggle to connect abstract scientific modeling concepts to their classroom practices.
3. They have strong TSE, and their CTC indicate readiness to integrate advanced technology into teaching.

Group 2 educators' high inquiry-learning scores may reflect an ability to foster exploratory and student-centered learning environments. This is consistent with the findings of Oh and Oh (2011), who highlight that, in science classrooms, there are science educators who effectively use models to demonstrate how natural processes work and to convey complex scientific concepts.

Key characteristics of science educators in group 3:

1. This group scores the highest across all constructs, reflecting an innovative, well-rounded, inquiry-driven teaching approach.

2. Their epistemological stance can be connected to some recent ideas from the philosophy of science that support student-centered, collaborative and context-grounded teaching practices.
3. The high scores in IL, CTC, and TSE suggest that they are able to foster environments where students actively engage with content, think critically, and use technology effectively.
4. Their strong performance in SMM indicates an ability to incorporate school scientific models and a variety of methods into their teaching.

## CONCLUSIONS

This study identified five latent constructs shaping Latin-American science educators' views on IBSE and CT: TM, IL, CTC, TSE, and SMM. Cluster analysis based on these constructs revealed three teacher profiles with distinct configurations of beliefs and practices.

Across the sample, TSE showed a moderately positive association with CTC ($r = 0.37$), suggesting that educators who feel more confident using digital technologies tend to hold clearer conceptions of CT and report stronger alignment with inquiry-oriented instructional practices.

The main contribution of this study lies in identifying empirically grounded teacher profiles that integrate epistemological views, inquiry practices, CTC, and TSE. Rather than treating these dimensions independently, the results show that they tend to cluster into coherent profiles of science educators. The profiling approach proposed here offers a useful analytical lens for understanding heterogeneity among science educators in Latin America and provides a practical basis for designing differentiated PD initiatives aimed at supporting the integration of CT within IBSE.

Several limitations should be acknowledged in this study. We relied on a convenience sample recruited through professional networks, which may have introduced self-selection bias and led to an overrepresentation of educators working in higher education. In addition, the exploratory design and the clustering approach were intended to identify patterns rather than establish causal relationships. Future research could extend this work by validating the identified profiles with larger and more representative samples, examining potential differences across educational levels, and conducting longitudinal studies to investigate how PD interventions may support transitions between teacher profiles and strengthen classroom implementation of CT-supported inquiry practices.

All these findings serve as a compelling argument in favor of the need for PD programs tailored to enhance science educators' understanding of CT and its role in fostering robust scientific inquiry. Such programs should also address the technological barriers and misconceptions that impede an effective integration of CT practices in classrooms. If the existing gaps are bridged, science educators could better equip students to engage with complex scientific phenomena, leveraging computational tools and modeling to deepen their understanding.

It would be interesting to focus future research on longitudinal studies assessing the impact of formative interventions like the ones that have been suggested in this article on both teacher practices and student learning outcomes. Analyses are needed to closely follow how the promises of CT in science education are fully realized in the Latin-American context.

Educational reforms in Latin America should consider the role of epistemological beliefs in adopting innovative teaching practices. "Transitioning" science educators (such as those in group 2) that want to move toward more contemporary teaching paradigms will require not only technical training, but also drastic reshaping in their theoretical frameworks regarding teaching, learning and the nature of science.

As we employed convenience sampling from the REDLAD association, this may limit the generalizability of our findings. For instance, this self-selection process resulted in a sample that included a larger proportion of respondents from higher education than from K-12 settings, which may further constrain the extent to which results reflect perspectives across all educational levels.

Because the sample includes educators from preschool to higher education, findings may reflect level-specific conditions (e.g., curriculum constraints, access to technology, and pedagogical expectations). Therefore, results should be interpreted as patterns across a mixed group of science educators rather than as level-specific conclusions for K-12 teachers.

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## REFERENCES

Aditomo, A., & Klieme, E. (2020). Forms of inquiry-based science instruction and their relations with learning outcomes: Evidence from high and low-performing education systems. *International Journal of Science Education, 42*(4), 504-525. https://doi.org/10.1080/09500693.2020.1716093

Adúriz-Bravo, A. (2013). A 'semantic' view of scientific models for science education. *Science & Education, 22*, 1593–1611. https://doi.org/10.1007/s11191-011-9431-7

Adúriz-Bravo, A. (2020). Contributions to the nature of science: Scientific investigation as inquiry, modeling, and argumentation. In C. N. El-Hani, M. Pietrocola, E. F. Mortimer, & M. R. Otero (Eds.), *Science education research in Latin America* (pp. 394–425). Brill/Sense. https://doi.org/10.1163/9789004409088_017

Amador-Rodríguez, R., Insuasty, D., Méndez-López, M., & Márquez, E. (2021). Promover modelos explicativos sobre las interacciones químicas del felodipino-citocromo P450: Una propuesta didáctica basada en la modelización [Promoting explanatory models on the chemical interactions of felodipine-cytochrome P450: A didactic proposal based on modeling]. *Química Nova, 44*(10), 1379–1387. https://doi.org/10.21577/0100-4042.20170784

Amador-Rodríguez, R., Insuasty, D., Méndez-López, M., Márquez, E., & Ospina-Quintero, N. (2023a). Explanatory models derived from context-based teaching: An investigation in undergraduate chemistry education. *Journal of Chemical Education, 100*(5), 1777-1787. https://doi.org/10.1021/acs.jchemed.2c01212

Amador-Rodríguez, R., Valencia Cobo, J. A., & Lozano, E. E. (2023b). Visiones sobre la naturaleza de la ciencia en docentes: Pistas para pensar cambios en su formación [Teachers' views on the nature of science: Clues for thinking about changes in their training]. *Revista Eureka sobre Enseñanza y Divulgación de las Ciencias, 20*(1), Article 1601. https://doi.org/10.25267/Rev_Eureka_ensen_divulg_cienc.2023.v20.i1.1601

Angeli, C., Voogt, J., Fluck, A., Webb, M., Cox, M., Malyn-Smit, J. H., & Zagami, J. (2016). A K-6 computational thinking curriculum framework: Implications for teacher knowledge. *Educational Technology & Society, 19*(3), 47-57.

Badillo, R. G., Miranda, R. P., de Gallego, L. N. T., & Amador-Rodríguez, R. Y. (2024). Pre-service science teacher education in Colombia. In M. R. Quintanilla Gatica & A. Adúriz-Bravo (Eds.), *Science teaching and a new teacher culture* (Vol. 31, pp. 151-170). Springer. https://doi.org/10.1007/978-3-031-50004-6_9

Bandura, A. (1990). Perceived self-efficacy in the exercise of personal agency. *Journal of Applied Sport Psychology, 2*(2), 128-163. https://doi.org/10.1080/10413209008406426

Bandura, A. (2006). Guide for creating self-efficacy scales. In F. Pajares, & T. C. Urdan (Eds.), *Self-efficacy beliefs of adolescents* (pp. 307-338). Information Age Publishing.

Barkley, E. F., Major, C. H., & Cross, K. P. (2014). *Collaborative learning techniques: A handbook for college faculty*. Jossey-Bass.

Barr, D., Harrison, J., & Conery, L. (2011). Computational thinking: A digital age skill for everyone. *Learning and Leading With Technology, 38*, 20-23.

Barrow, L. H. (2006). A brief history of inquiry: From Dewey to standards. *Journal of Science Teacher Education, 17*(3), 265-278. https://doi.org/10.1007/s10972-006-9008-5

Bell, T., & Vahrenhold, J. (2018). CS unplugged—How is it used, and does it work? In H.-J. Böckenhauer, D. Komm, & W. Unger (Eds.), *Adventures between lower bounds and higher altitudes: Essays dedicated to Juraj Hromkovič on the occasion of his 60th birthday* (pp. 497-521). Springer. https://doi.org/10.1007/978-3-319-98355-4_29

Belmar, H. (2022). Review on the teaching of programming and computational thinking in the world. *Frontiers in Computer Science, 4*. https://doi.org/10.3389/fcomp.2022.997222

Berland, L. K., & McNeill, K. L. (2010). A learning progression for scientific argumentation: Understanding student work and designing supportive instructional contexts. *Science Education, 94*(5), 765-793. https://doi.org/10.1002/sce.20402

Bers, M. U. (2020). *Coding as a playground: Programming and computational thinking in the early childhood classroom*. Routledge. https://doi.org/10.4324/9781003022602

Boulden, D. C., Rachmatullah, A., Oliver, K. M., & Wiebe, E. (2021). Measuring in-service teacher self-efficacy for teaching computational thinking: Development and validation of the T-STEM CT. *Education and Information Technologies, 26*(4), 4663-4689. https://doi.org/10.1007/s10639-021-10487-2

Brown, P. L., Abell, S. K., Demir, A., & Schmidt, F. J. (2006). College science teachers' views of classroom inquiry. *Science Education, 90*(5), 784–802. https://doi.org/10.1002/sce.20151

Bybee, R. (2011). Scientific and engineering practices in K-12 classrooms. *Science Teacher, 78*(9), 34-40.

Cairns, D. (2019). Investigating the relationship between instructional practices and science achievement in an inquiry-based learning environment. *International Journal of Science Education, 41*(15), 2113-2135. https://doi.org/10.1080/09500693.2019.1660927

Cakir, M. (2011). L. B. Flick and N. G. Lederman (eds): *Scientific inquiry and nature of science: Implications for teaching, learning, and teacher education*. *Science & Education, 20*(3-4), 381-387. https://doi.org/10.1007/s11191-010-9274-7

Castillo-Hernández, F.-J., Jiménez-Liso, M.-R., & Couso, D. (2022). Can we do real inquiry online? Influence of real-time data collection on students' views of inquiry in an online, multi-site masters' degree on environmental education. *Journal of Computing in Higher Education, 34*(3), 608-632. https://doi.org/10.1007/s12528-022-09312-7

Chaia, A., Child, F., Dorn, E., Frank, M., & Krawitz, M. (2017). *Drivers of student performance: Latin America insights*. McKinsey&Company.

Couso, D. (2014). Lagarón, D. C. (2015). De la moda de "aprender indagando" a la indagación para modelizar: Una reflexión crítica [From the trend of "learning by inquiring" to inquiry for modeling: A critical reflection]. In *Proceedings of the 26th International Symposium on Didactics of Social Sciences*.

Dabholkar, S., Arastoopour Irgens, G., Horn, M., & Wilensky, U. (2020). Students' epistemic connections between science inquiry practices and disciplinary ideas in a computational science unit. In *Proceedings of the International Conference of the Learning Sciences*.

Deci, E., & Ryan, R. (2004). *Handbook of self-determination research*. University Rochester Press.

Develaki, M. (2017). Using computer simulations for promoting model-based reasoning: Epistemological and educational dimensions. *Science & Education, 26*(7-9), 1001-1027. https://doi.org/10.1007/s11191-017-9944-9

Diordieva, C., Yeter, I. H., & Smith, W. (2019). Middle school STEM teachers' understandings of computational thinking: A case study of Brazil and the USA. In *Proceeding of the American Society for Engineering Education Conference & Exposition*. https://doi.org/10.18260/1-2--33107

Espinal, A., Vieira, C., & Guerrero-Bequis, V. (2023). Student ability and difficulties with transfer from a block-based programming language into other programming languages: A case study in Colombia. *Computer Science Education*, *33*(4), 567–599. https://doi.org/10.1080/08993408.2022.2079867

Espinal, A., Vieira, C., & Magana, A. J. (2024). Professional development in computational thinking: A systematic literature review. *ACM Transactions on Computing Education*, *24*(2), Article 27. https://doi.org/10.1145/3648477

Farris, A. V., Dickes, A. C., & Sengupta, P. (2016). Development of disciplined interpretation using computational modeling in the elementary science classroom. In *Proceedings of the 12th International Conference of the Learning Sciences* (pp. 282-289).

Feyerabend, P. (1975). 'Science.' The myth and its role in society. *Inquiry, 18*(2), 167-181. https://doi.org/10.1080/00201747508601758

Furber, S. (2012). Shut down or restart? The way forward for computing in UK schools. *The Royal Society*. https://royalsociety.org/-/media/education/computing-in-schools/2012-01-12-computing-in-schools.pdf

Gillies, R. M., & Baffour, B. (2017). The effects of teacher-introduced multimodal representations and discourse on students' task engagement and scientific language during cooperative, inquiry-based science. *Instructional Science, 45*(4), 493-513. https://doi.org/10.1007/s11251-017-9414-4

Gómez, R. L., & Suárez, A. M. (2020). Do inquiry-based teaching and school climate influence science achievement and critical thinking? Evidence from PISA 2015. *International Journal of STEM Education, 7*(1), Article 43. https://doi.org/10.1186/s40594-020-00240-5

Hodson, D. (2003). Time for action: Science education for an alternative future. *International Journal of Science Education*, *25*(6), 645-670. https://doi.org/10.1080/09500690305021

Izquierdo-Aymerich, M., & Adúriz-Bravo, A. (2003). Epistemological foundations of school science. *Science & Education*, *12*(1), 27–43. https://doi.org/10.1023/A:1022698205904

Izquierdo Aymerich, M., & Adúriz-Bravo, A. (2021). Contribuciones de Giere a la reflexión sobre la educación científica [Giere's contributions to the reflection on science education]. *ArtefaCToS. Revista de Estudios Filosóficos sobre Ciencia y Tecnología*, *10*(1), 75–87. https://doi.org/10.14201/art20211017587

Jiménez Aleixandre, M. P. (2012). Las prácticas científicas en la investigación y en la clase de ciencias [Scientific practices in research and in the science classroom]. In Proceedings of the 25th Meetings on the Didactics of Experimental Sciences (pp. 9-15). APICE/University of Santiago de Compostela.

Justi, R., & Gilbert, J. (2003). Teachers' views on the nature of models. *International Journal of Science Education, 25*(11), 1369-1386. https://doi.org/10.1080/0950069032000070324

Katai, Z. (2020). Promoting computational thinking of both sciences- and humanities-oriented students: An instructional and motivational design perspective. *Educational Technology Research and Development, 68*(5), 2239-2261. https://doi.org/10.1007/s11423-020-09766-5

Kelly, G. J. (2008). Inquiry, activity and epistemic practice. In J. S. Lederman (Ed.), *Teaching scientific inquiry* (pp. 99-117). Cengage. https://doi.org/10.1163/9789460911453_009

Kelly, G. J. (2014). Inquiry teaching and learning: Philosophical considerations. In M. Matthews (Eds.), *International handbook of research in history, philosophy and science teaching* (pp. 1363-1380). Springer. https://doi.org/10.1007/978-94-007-7654-8_42

Ketelhut, D. J. (2007). The impact of student self-efficacy on scientific inquiry skills: An exploratory investigation in River City, a multi-user virtual environment. *Journal of Science Education and Technology, 16*(1), 99-111. https://doi.org/10.1007/s10956-006-9038-y

Kite, V., & Park, S. (2023). What's computational thinking?: Secondary science teachers' conceptualizations of computational thinking (CT) and perceived barriers to CT integration. *Journal of Science Teacher Education, 34*(4), 391-414. https://doi.org/10.1080/1046560X.2022.2110068

Klemencic, M. (2015). 'What is student agency? An ontological exploration in the context of research on student engagement.' In M. Klemencic, S. Bergan, & R. Primozic (Eds.), *Student engagement in Europe: Society, higher education and student governance* (pp. 11-29). Council of Europe.

Lee, I., Martin, F., Denner, J., Coulter, B., Allan, W., Erickson, J., Malyn-Smith, J., & Werner, L. (2011). Computational thinking for youth in practice. *ACM Inroads, 2*(1), 32-37. https://doi.org/10.1145/1929887.1929902

Liang, L. L., Chen, S., Chen, X., Kaya, O. N., Adams, A. D., Macklin, M., & Ebenezer, J. (2009). Preservice teachers' views about nature of scientific knowledge development: An international collaborative study. *International Journal of Science and Mathematics Education, 7*(5), 987-1012. https://doi.org/10.1007/s10763-008-9140-0

Mouza, C., Yang, H., Pan, Y.-C., Yilmaz Ozden, S., & Pollock, L. (2017). Resetting educational technology coursework for pre-service teachers: A computational thinking approach to the development of technological pedagogical content knowledge (TPACK). *Australasian Journal of Educational Technology, 33*(3), 61-76. https://doi.org/10.14742/ajet.3521

National Research Council. (1996). *National science education standards*. The National Academies Press.

National Research Council. (2000). *Inquiry and the national science education standards*. The National Academies Press.

National Research Council. (2012). *A framework for K-12 science education: Practices, crosscutting concepts, and core* ideas. The National Academies Press.

OECD. (2019). *PISA 2018 assessment and analytical framework*. OECD Publishing. https://doi.org/10.1787/b25efab8-en

Ogegbo, A. A., & Ramnarain, U. (2022). Teachers' perceptions of and concerns about integrating computational thinking into science teaching after a professional development activity. *African Journal of Research in Mathematics, Science and Technology Education, 26*(3), 181-191. https://doi.org/10.1080/18117295.2022.2133739

Oh, P. S., & Oh, S. J. (2011). What teachers of science need to know about models: An overview. *International Journal of Science Education, 33*(8), 1109-1130. https://doi.org/10.1080/09500693.2010.502191

Passmore, C., Gouvea, J. S., & Giere, R. (2014). Models in science and in learning science: Focusing scientific practice on sense-making. In M. R. Matthews (Ed.), *International handbook of research in history, philosophy and science teaching* (pp. 1171-1202). Springer. https://doi.org/10.1007/978-94-007-7654-8_36

Psycharis, S., Kalovrektis, K., Xenakis, A., Paliokas, I., Patrinopoulos, M., Georgiakakis, P., Iatrou, P., Theodorou, P., Papageorgiou, T., & Ntourou, V. (2021). The impact of physical computing and computational pedagogy on girl's self-efficacy and computational thinking practice. In *2021 IEEE Global Engineering Education Conference* (pp. 308-315). IEEE. https://doi.org/10.1109/EDUCON46332.2021.9454003

Sandoval, W. A., & Reiser, B. J. (2004). Explanation-driven inquiry: Integrating conceptual and epistemic scaffolds for scientific inquiry. *Science Education, 88*(3), 345-372. https://doi.org/10.1002/sce.10130

Sengupta, P., Dickes, A., & Farris, A. (2018). Toward a phenomenology of computational thinking in STEM education. In M. Khine (Eds.), *Computational thinking in the STEM disciplines* (pp. 49-72). Springer. https://doi.org/10.1007/978-3-319-93566-9_4

Sengupta, P., Kinnebrew, J. S., Basu, S., Biswas, G., & Clark, D. (2013). Integrating computational thinking with K-12 science education using agent-based computation: A theoretical framework. *Education and Information Technologies, 18*(2), 351-380. https://doi.org/10.1007/s10639-012-9240-x

Sherwood, H., Culp, K. M., Ferguson, C., Kaiser, A., Henry, M., & Negron, A. (2024). Teacher practices for formatively assessing computational thinking with early elementary learners. *Education Sciences, 14*(11), Article 1250. https://doi.org/10.3390/educsci14111250

Sulistiyo, M. A. S., & Wijaya, A. (2020). The effectiveness of inquiry-based learning on computational thinking skills and self-efficacy of high school students. *Journal of Physics: Conference Series, 1581*, Article 012046. https://doi.org/10.1088/1742-6596/1581/1/012046

Taber, K. S. (2018). The use of Cronbach's alpha when developing and reporting research instruments in science education. *Research in Science Education, 48*(6), 1273-1296. https://doi.org/10.1007/s11165-016-9602-2

Tsakeni, M. (2021). Preservice teachers' use of computational thinking to facilitate inquiry-based practical work in multiple-deprived classrooms. *Eurasia Journal of Mathematics, Science and Technology Education, 17*(1), Article em1933. https://doi.org/10.29333/ejmste/9574

Vieira, C., Espinal, A., Chiu, J., Bredder, E., Harris, P. & Wilkens, K. (2024) Hacia una educación equitativa en ciencias de la computación [Towards equitable education in computer science]. *Revista EIA*, *21*(42), Article 4210. https://doi.org/10.24050/reia.v21i42.1734

Vieira, C., Gómez, R. L., Gómez, M., Canu, M., & Duque, M. (2023). Implementing unplugged CS and use-modify-create to develop student computational thinking skills: A nationwide implementation in Colombia. *Educational Technology & Society*, *26*(3), 155-175. https://doi.org/10.30191/ETS.202307_26(3).0012

Vieira, C., Magana, A. J., & Boutin, M. (2018a). Add-on preferential groups (APG): Analyzing student preferences of teaching methods. *Computer Applications in Engineering Education*, *26*(4), 1020–1032. https://doi.org/10.1002/cae.21953

Vieira, C., Magana, A. J., García, R. E., Jana, A., & Krafcik, M. (2018b). Integrating computational science tools into a thermodynamics course. *Journal of Science Education and Technology*, *27*(4), 322-333. https://doi.org/10.1007/s10956-017-9726-9

Vieira, C., Magana, A. J., Roy, A., & Falk, M. L. (2019). Student explanations in the context of computational science and engineering education. *Cognition and Instruction*, *37*(2), 201–231. https://doi.org/10.1080/07370008.2018.1539738

Weintrop, D., Beheshti, E., Horn, M., Orton, K., Jona, K., Trouille, L., & Wilensky, U. (2016). Defining computational thinking for mathematics and science classrooms. *Journal of Science Education and Technology*, *25*(1), 127-147. https://doi.org/10.1007/s10956-015-9581-5

Wilkerson, M. H., Shareff, R., Laina, V., & Gravel, B. (2018). Epistemic gameplay and discovery in computational model-based inquiry activities. *Instructional Science*, *46*(1), 35-60. https://doi.org/10.1007/s11251-017-9430-4

Yadav, A., Stephenson, C., & Hong, H. (2017). Computational thinking for teacher education. *Communications of the ACM, 60*(4), 55-62. https://doi.org/10.1145/2994591

## APPENDIX A

Q1. Mathematical language allows describing and explaining reality as it is, generating scientific knowledge.

Q2. In my classes I teach that the natural sciences advance because scientists choose the best scientific model, the one most similar to the phenomenon being studied.

Q3. In my classes I teach that scientists create laws, hypotheses, models or theories to describe what happens in nature.

Q4. The decision for one model or another is not only based on the resemblance or similarity with nature.

Q5. Scientists performing research start with the observation of phenomena, then proceed to formulate hypotheses, design and perform experiments, and finally draw conclusions containing more information than the original hypotheses.

Q6. Experimental designs proposed by scientists as their observations are mediated by their scientific models, which also guide decision-making.

Q7. In my classes I teach that many scientific models used in research laboratories (such as the model of heat, neurons, DNA or the atom) are similar or similar to reality.

Q8. Scientific models are similar to phenomena that occur in nature

Q9. In my classes I teach that scientists do not use the same procedure when they investigate, they always use different methodologies, according to their research interests.

Q10. In scientific activity, the relationship between scientific model and experimental designs is subject to the decisions that scientists make during their research.

Q11. Theories or hypotheses are proved or verified when it is possible to carry out empirical experiments and/or observations in accordance with what is expressed in them.

Q12. In my classes I teach that scientists propose scientific models, which are similar to reality because they represent, explain and predict phenomena.

Q13. Scientific models mediate between a theory and nature, allowing scientists to probe and explain nature.

Q14. Observation and experimentation provide a secure base from which scientific knowledge can be derived.

Q15. Scientific advancement is based on the accumulation of theories, whereby new theories incorporate previous ones both conceptually and methodologically.

Q16. In my classes I teach that scientists choose one scientific model over another because the one they select allows them to represent, explain and predict phenomena better than another model.

Q17. The choice of one scientific model over another is due to human interests (professional, social, etc.); it is a decision that exceeds the interest in just knowing nature.

Q18. Theories are formulated as a system of statements that are susceptible of an interpretation based on observation and/or experimentation.

Q19. In my classes I promote that students have the opportunity to explain their ideas.

Q20. In my classes, I encourage students to spend time in the lab doing hands-on experiments.

Q21. In my classes I cause students to discuss school science topics.

Q22. In my classes I encourage students to draw conclusions from experiments that they themselves have carried out.

Q23. In my classes I explain how an idea can be applied to different phenomena of nature.

Q24. In my classes I encourage students to design their own experiments.

Q25. In my classes I promote debates about scientific investigations.

Q26. I clearly explain the relevance of the concepts, theories and/or models of science for our lives.

Q27. In my classes I ask students to carry out experimental work, information searches, making models, argumentative, etc., to check the ideas presented in class.

Q28. I know how to solve technical problems when the technology fails.

Q29. I can easily learn about new technologies.

Q30. I always seek support of my Tech colleagues to solve technical problems.

Q31. Technology will always help students learn better.

Q32. I know how to use technology with students in class.

Q33. I stay up to date about new technologies to support learning.
Q34. Technologies should be integrated into the classroom practices because they are a global trend.
Q35. Creating spreadsheets.
Q36. Using a computer.
Q37. Designing websites.
Q38. Task automation.
Q39. Creating and using models and simulations.
Q40. Data processing.
Q41. Computational problem-solving.
Q42. Robot programming.
Q43. Using augmented reality.
Q44. Applying logic.

## APPENDIX B

**Table B1.** Factor loadings for all items and factors

| Item | MR1 | MR2 | MR3 | MR4 | MR5 |
|---|---|---|---|---|---|
| Q14 | 0.85 | 0.06 | 0.05 | -0.12 | 0.05 |
| Q11 | 0.79 | 0.01 | 0.14 | 0.06 | 0.06 |
| Q5 | 0.73 | 0.10 | 0.14 | -0.03 | 0.15 |
| Q15 | 0.67 | 0.01 | 0.12 | 0.15 | 0.01 |
| Q1 | 0.66 | -0.09 | 0.21 | -0.12 | 0.16 |
| Q3 | 0.66 | 0.07 | 0.26 | 0.16 | 0.16 |
| Q12 | 0.66 | 0.15 | 0.11 | 0.29 | 0.05 |
| Q18 | 0.65 | 0.13 | 0.10 | 0.25 | 0.21 |
| Q2 | 0.64 | -0.04 | 0.21 | 0.21 | -0.01 |
| Q7 | 0.55 | 0.19 | 0.13 | 0.21 | 0.04 |
| Q6 | 0.41 | 0.14 | 0.01 | 0.40 | 0.07 |
| Q22 | 0.11 | 0.84 | 0.05 | 0.04 | 0.04 |
| Q25 | -0.05 | 0.78 | 0.07 | 0.17 | -0.04 |
| Q19 | -0.03 | 0.76 | 0.11 | 0.06 | 0.17 |
| Q21 | -0.03 | 0.74 | 0.13 | 0.10 | 0.12 |
| Q24 | -0.07 | 0.71 | 0.19 | 0.10 | -0.14 |
| Q20 | 0.18 | 0.69 | -0.01 | -0.05 | 0.00 |
| Q23 | 0.19 | 0.68 | 0.11 | 0.19 | 0.26 |
| Q27 | 0.10 | 0.65 | 0.03 | 0.04 | 0.01 |
| Q26 | 0.26 | 0.55 | -0.02 | 0.33 | 0.19 |
| Q41 | 0.21 | 0.25 | 0.79 | 0.11 | 0.09 |
| Q40 | 0.21 | 0.10 | 0.73 | 0.11 | 0.04 |
| Q44 | 0.20 | 0.03 | 0.67 | 0.18 | 0.26 |
| Q38 | 0.24 | 0.07 | 0.65 | -0.09 | 0.17 |
| Q39 | 0.20 | 0.12 | 0.59 | 0.15 | 0.23 |
| Q10 | 0.25 | 0.09 | 0.10 | 0.74 | -0.03 |
| Q9 | 0.04 | 0.15 | -0.05 | 0.69 | 0.14 |
| Q16 | 0.32 | 0.14 | 0.18 | 0.59 | 0.03 |
| Q17 | 0.00 | 0.07 | 0.15 | 0.47 | 0.13 |
| Q32 | 0.20 | 0.12 | 0.16 | 0.15 | 0.83 |
| Q33 | 0.12 | 0.19 | 0.30 | 0.03 | 0.66 |
| Q28 | 0.14 | 0.00 | 0.20 | 0.15 | 0.65 |