MODESTUM EURASIA Journal of Mathematics, Science and Technology Education, 2026, 22(12), em2963
ISSN:1305-8223 (online)
OPEN ACCESS Research Paper https://doi.org/10.29333/ejmste/19895

Mapping educational robotics competencies for pre-service teachers in science course: An exploratory sequential mixed-methods study

M. Anas Thohir [1*], Nurul Istiq'faroh [2], Awaluddin Hidayat Ramli Inaku [3], Anisa Wahyu Kusumaningtyas [4], Weahason Weahama [5]

[1] Department of Elementary and Preschool Education, Universitas Negeri Malang, Malang, INDONESIA
[2] Faculty of Education, Universitas Negeri Surabaya, Surabaya, INDONESIA
[3] Department of Environmental Science, Faculty of Engineering and Science, Universitas Pembangunan Nasional "Veteran" Jawa Timur, Surabaya, INDONESIA
[4] Faculty of Teacher Training and Education, Universitas Sebelas Maret, Surakarta, INDONESIA
[5] Faculty of Education, Prince of Songkla University, Songkhla, THAILAND

Received 28 July 2026 ▪ Accepted 26 October 2026

Abstract

Educational robotics is increasingly used to develop pre-service elementary teachers' computational thinking (CT), yet limited empirical evidence exists on the competencies required for robotics-integrated teaching. This exploratory sequential mixed-methods study identified robotics-related perceived competencies and examined the relationships among CT, technological pedagogical content knowledge (TPACK), and robotics pedagogical content knowledge (RPCK). Qualitative data from 128 pre-service teachers were analyzed using inductive thematic analysis, followed by a survey of 150 participants analyzed with partial least squares structural equation modeling. The qualitative phase identified 22 perceived competencies grouped into CT, TPACK, RPCK, and complementary professional domains, with digital technology literacy, creativity, and problem-solving emerging most frequently. The quantitative results showed that abstraction and algorithmic thinking were associated with TPACK, whereas decomposition and debugging were associated with RPCK. TPACK showed the strongest association with RPCK. Generalization was excluded from the structural analysis because of insufficient discriminant validity. These findings provide an exploratory and empirically informed mapping of pre-service teachers' perceived competencies robotics-integrated science teaching and preliminary evidence of associations among selected dimensions of CT, TPACK, and RPCK. The complementary and emergent domain identified in the qualitative phase requires further quantitative examination.

Keywords: computational thinking, technological pedagogical content knowledge, pre-service teacher, robotic education, exploratory sequential mixed-methods

INTRODUCTION

Computational thinking (CT) has become a core competency for students and teachers in the digital age (Angeli, 2022; Bakala et al., 2021; Falloon, 2024). Many countries have incorporated CT into their national curricula to prepare students for an increasingly technology-driven society (Belmar, 2022; Pajchel et al., 2024). CT enables learners to formulate problems, design algorithms, decompose complex tasks, and develop systematic solutions across science, technology, engineering, and mathematic (STEM) disciplines (Belmar, 2022; Falloon, 2024; Proctor, 2023). One challenge in integrating coding, artificial intelligence (AI), and CT into elementary science education lies in the abstract nature of these concepts. This creates a challenge in elementary education, where students are predominantly in Piaget's concrete operational stage

© 2026 by the authors; licensee Modestum. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution License (https://creativecommons.org/licenses/by/4.0/).
✉ anas.thohir.fip@um.ac.id **(*Correspondence)** ✉ nurulistiqfaroh@unesa.ac.id ✉ awaluddin_hidayat.mling@upnjatim.ac.id
✉ anisawkusumaningtyas@student.uns.ac.id ✉ Weahason.w@psu.ac.th

Contribution to the literature

- This study extends the literature on educational robotics by identifying 22 competencies perceived as necessary for robotics-based science learning among prospective elementary school teachers. These competencies encompass four domains: CT, TPACK, RPCK, and complementary and emergent professional competencies.
- It contributes empirical evidence regarding the differentiated associations of CT dimensions with TPACK and RPCK. Abstraction and algorithmic thinking were significantly associated with TPACK, whereas decomposition and debugging were significantly associated with RPCK.
- It provides preliminary evidence of a positive association between TPACK and RPCK, indicating that broader technological pedagogical competence is closely related to robotics-specific PCK.

and learn more effectively through direct manipulation of tangible objects and experiences (Slavin, 2018; Woolfolk, 2016). In science education, hands-on experimentation plays a central role in facilitating conceptual understanding (Moore et al., 2020). Constructionism further extends this view by emphasizing the creation of concrete artifacts as a means of making abstract ideas visible and meaningful (Hosseini, 2015; Papert & Harel, 2002). Instead of learning the core processes of CT in the form of abstract concepts, learners physically perform them through activities such as designing sequential instructions, making smaller steps to solve problems, and debugging the code when the robot does not do what it is supposed to. Direct engagement with educational robotics (ER) is especially important for pre-service teachers, as it enhances their own CT competence and pedagogically prepares them to subsequently implement similar CT-building activities with their future elementary students.

Accordingly, ER has emerged as an effective learning approach for developing these competencies. Robotic activities combine programming, engineering design, and hands-on problem-solving in authentic learning environments (Lampropoulos, 2025; Martínez Rojas et al., 2025; Moreno-Palma et al., 2025). In addition, ER offers a promising approach for integrating technology into science learning by transforming abstract concepts (Ching & Hsu, 2024; Fung et al., 2025; Nannim et al., 2024; Scaradozzi et al., 2019). Teachers play a central role implementing ER to foster students' CT. Therefore, the successful integration of ER requires pre-service teachers to possess competencies in CT, pedagogy, and technology integration.

Despite growing interest in ER, its integration into elementary science teaching remains challenging. Addressing this challenge requires pre-service elementary school teachers (PESTs) to develop technological pedagogical content knowledge (TPACK) for effectively integrating technology, pedagogy, and science content (Mishra & Koehler, 2006). Previous studies have investigated CT alongside TPACK (e.g., Kong et al., 2020; Umutlu, 2022), explored CT in teacher education contexts (Lane et al., 2023; Yadav et al., 2014), and emphasized teachers' professional development and self-efficacy (Macann et al., 2026). More recently, Hsu and Tsai (2024) demonstrated that CT directly predicts robotics pedagogical content knowledge (RPCK), with robotics teaching beliefs serving as a mediator. However, several important gaps remain. First, previous studies have focused on predefined constructs, overlooking competencies emerging from PESTs' robotics experiences. Unlike conventional digital technologies, ER requires teachers to integrate robotics hardware, programming, engineering design, CT, and problem-solving into meaningful pedagogical practices (Isnaini et al., 2019; Puzio, 2025). When mapped onto the TPACK framework, these competencies may place PESTs at the "re-novicing" level (Lane et al., 2023). Second, despite the close conceptual relationship between CT and technology integration, little empirical evidence explains how CT contributes to RPCK. Therefore, Yanış and Yürük (2021) extended the TPACK framework by proposing educational robotics technological pedagogical content knowledge (ER-TPACK). Third, systematic reviews have highlighted the need for empirically validated conceptual models and more evidence focusing on pre-service teacher education. Addressing these gaps, the present study adopts an exploratory sequential mixed-methods design to identify empirically derived robotics-related competencies, organize them into theoretically meaningful domains (CT, TPACK, RPCK, and complementary competencies), and subsequently examine associations among selected CT dimensions, TPACK, and RPCK.

This study aims to develop an empirically informed mapping of perceived competencies of perceived competencies for robotics-integrated teaching among PESTs. Specifically, the study first identifies the competencies that emerge from pre-service teachers' experiences in robotics learning through an exploratory qualitative analysis, maps these competencies into the conceptual domains of CT, TPACK, RPCK, and subsequently examines the structural relationships among these constructs using partial least squares structural equation modeling (PLS-SEM). By integrating exploratory qualitative inquiry with quantitative model examination, this study contributes to the literature by

providing an empirically derived competency framework. This study also extend understanding of the pedagogical association between TPACK and RPCK in relation to selected CT dimensions and offering a context-specific model to inform robotics-integrated teacher education.

CT in PEST

Since it was popularized by Wing (2006), CT has developed a lot and is integrated with other materials. CT is a way of thinking about solving problems in the way used by computer experts (Wing, 2006, 2017). In 1980, this concept was first introduced by Seymour Papert who emphasized not only methods but also ways of thinking about problem-solving both in the field of computers and other fields (Wing, 2006). In fact, the International Society for Technology in Education also integrates CT into the school learning curriculum for students and teachers (Crompton & Sykora, 2021). Then, this way of thinking is often integrated in the fields of STEM (C. Wang et al., 2022; Cheng et al., 2023; Y. Li et al., 2020). Robotic learning is also often linked to cursors using robots. Noh and Lee (2020) reports that robotics programming courses can improve CT and creativity. In addition, Budiyanto et al. (2022) also added CT could increase because STEM activities in robotics reflect the skills themselves. Then, Yadav et al. (2017) modelling the relationship between materials, strategies, and CT trainer partners to prepare teachers as CT teachers. However, the educational element and how much contribution CT has made in pedagogical integration has not been clearly revealed. The relationship needs to be revealed by looking for the effects of each CT indicator (C.-Y. Hsu & Tsai, 2024). In addition, the study has not revealed in detail CT related to pedagogy through or RPCK in prospective elementary school teachers. Measurements were taken to determine CT's knowledge of operating the robot based on CT's self-efficacy response.

Several studies have outlined indicators of CT mechanisms for pre-service teachers (Angeli, 2022; Avcı & Deniz, 2022; Q. Li, 2021; S.-C. Kong & Lai, 2022). First Wing (2006) explains that thinking like a computer expert requires solving problems, designing systems, thinking recursively, abstraction, and decomposition. Then, Grover and Pea (2013) breaking it down into many indicators, such as abstractions and pattern generalizations, systematic processing, algorithmic notions, decomposition, and debugging. Avcı and Deniz (2022) also present the competencies of CT PESTs and preschool teachers, such as problem-solving, heuristics, logical thinking, programming. Then W. Dong et al. (2024a) also conducted an analysis related to 9 types of CT including: creative thinking, critical thinking, abstraction, debugging, decomposition, algorithmic thinking, problem-solving, coding, and concept understanding. CT measurements using existing indicators are certainly useful in overcoming several problems. For example, the adaptability of robots, ER, the development of individual learning programs, and collaborative online learning arrangements are some of the solutions in dealing with CT problems (Kerimbayev et al., 2023).

ER as a Constructionist Learning Environment

ER is a specific field of science that involves robots either with the construction or deconstruction of hardware and programming to explore materials, environments, activities, skills, and knowledge (Scaradozzi et al., 2019). Rooted in Papert's constructionism theory, ER emphasizes learning through the creation of tangible artifacts, enabling students to develop knowledge and understanding through hands-on experiences (Papert, 1993, 2020; Papert & Harel, 2002). This theory is widely used in robotic learning as a reinforcement of STEM, 21st century skills, and also the achievement of the sustainable development goals (SDGs) (Alam & Mohanty, 2024; Bou Saad et al., 2025; Haidegger et al., 2023; Lu et al., 2025; Su et al., 2025). In addition, hand-on learning is also a support for STEM literacy to transform from just abstract concepts to real product solutions (Christensen et al., 2015; Okundaye et al., 2022). The integration of robots into science learning is a real alternative to introduce AI, STEM, and SDGs (Bai & Tian, 2025; Henze et al., 2022; Zollman, 2012). Even, S. Dong et al. (2025) applied the principles of robotic constructionism to students and demonstrated a tangible contribution to cognitive skills, critical thinking, hands-on learning, and innovative design skills based on educational robots.

ER is likely to be a good alternative to teaching coding and AI such as Machine learning and humanoid robots (Eguchi, 2022, 2023; M. Thamrin et al., 2026). In the integration of robotics in learning, pre-service teachers can adopt robots through software design and hardware (Bellas et al., 2024). Both require specific skills, hardware leads to a series of microcontrollers, sensors, and 3D printer designs. Then, the software learns about programming commands to robots through a certain number of codes through applications, such as Scrate MIT, Arduino IDE, and Python. This specific knowledge is then referred to as robot knowledge. As Eguchi (2023) provides a variety of AI-based robot alternatives that can be learned in robotics courses. This validates that robotics courses train a variety of thinking skills in solving robot projects, such as 21st century skills (Eguchi, 2014), CT (Budiyanto et al., 2022; Jamal et al., 2024; Lee et al., 2025; Qu & Fok, 2022), creativity (Noh & Lee, 2020), and self-efficacy (Avcı & Deniz, 2022). In addition, robotic knowledge can be integrated into the pedagogy of pre-service teachers. Thus, this study needs to explore the contribution of CT to be able to associate the role in integrating robotics in learning.

TPACK and RPCK

TPACK is a framework that provides a useful foundation for integrating technology into instruction. This framework is proposed by Mishra and Koehler (2006) extends Shulman's (1987) pedagogical content knowledge (PCK) framework by incorporating technological knowledge (TK) into teaching and learning. The concept of TPACK itself is divided into several components such as content knowledge (CK), pedagogical knowledge (PK), TK, technological content knowledge, technological pedagogical knowledge, PCK, to become a unit, namely TPACK (Mishra & Koehler, 2006). Although originally proposed to support the integration of digital technologies into classroom instruction, the TPACK framework has evolved to address emerging educational demands, including AI (Celik, 2023; Setiyawan et al., 2025), CT education (Dolgopolovas & Dagiene, 2024; MacCallum, 2025), and ER (Hu et al., 2023). Therefore, contemporary studies increasingly view TPACK as a dynamic and adaptable framework for developing teachers' professional competencies in response to rapidly evolving educational technologies.

Although TPACK provides a comprehensive framework for technology integration, it does not explicitly address the specialized competencies required for ER. Unlike conventional digital technologies, ER requires teachers to integrate robotics hardware, programming, engineering design, CT, and problem-solving into meaningful pedagogical practices (Isnaini et al., 2019; Puzio, 2025). For example, teaching simple machines requires teachers to apply technical skills in constructing a robotic arm as well as pedagogical strategies to enable students to relate its movement to scientific concepts. Similarly, in a lesson on energy transfer, teachers need to help students program a robot to move while also supporting their comprehension of the science concepts involved. These interdisciplinary demands extend beyond the scope of the original TPACK framework, as teachers must not only integrate technology with pedagogy and content but also facilitate robotics-specific learning experiences that combine technical and cognitive competencies. Therefore, Yanış and Yürük (2021) extended the TPACK framework by proposing ER-TPACK, which incorporates the specialized TK, PK, and CK required for robotics-based instruction. Building on the work of preview research (Chu et al., 2020), Hsu and Tsai (2024) further refined the ER-TPACK framework by introducing RPCK, which emphasizes the PK required for effective robotics instruction. Recent research has increasingly positioned RPCK as a domain-specific extension of the TPACK framework for ER. This conceptual development not only reflects the specialized knowledge required for robotics instruction but also provides a theoretical foundation for investigating the relationships among TPACK, CT, and RPCK.

In this study, CT, TPACK, and RPCK are conceptualized as interrelated dimensions of competence rather than mutually exclusive categories. CT involves computational approaches to problem-solving, including abstraction, decomposition, algorithmic thinking, and debugging (Angeli & Jaipal-Jamani, 2018; W. Dong et al., 2024). whereas TPACK concerns the integration of TK, PK, and CK to support teaching and learning (Angeli & Valanides, 2013; Mishra & Koehler, 2006). RPCK, as operationalized in this study, focuses on the pedagogical integration of robotics with disciplinary content, particularly the design of robotics-supported learning activities and the use of robotics to facilitate students' understanding of science concepts (C. Y. Hsu & Tsai, 2024). In the qualitative analysis, competencies were classified according to what participants primarily described in their responses. This distinction was important because a competency could relate to more than one construct, depending on its context. For instance, programming was associated with CT when participants discussed developing algorithms or debugging code, whereas it was linked to RPCK when they described using programming to design robotics-based science learning activities. This distinction recognizes that teaching science with robotics involves more than computational or technical skills; it also requires teachers to connect these skills with pedagogical strategies and science content. The resulting mapping therefore represents how the reported competencies relate to CT, TPACK, and RPCK, rather than assigning each competency exclusively to one construct.

Moreover, most studies still focus the integration of robotics and CT on technical aspects or student learning outcomes (Kert et al., 2020; T.-C. Hsu & Chen, 2025; Vasconcelos et al., 2025; W. Yang, 2025), without explicitly linking it to the TPACK framework and its expansion such as RPCK in the education of prospective elementary school teachers. In addition, the use of robotics in education is very common and addresses critical gaps in STEM education (H. Wang et al., 2024; Zviel-Girshin & Rosenberg, 2025). Thus, we has several conjectures as follows, and hypothetical research shown in **Figure 1**. Accordingly, the following hypotheses were proposed:

- **H1:** Abstraction is positively associated with pre-service teachers' TPACK.
- **H2:** Abstraction is positively associated with pre-service teachers' RPCK.
- **H3:** Generalization is positively associated with pre-service teachers' TPACK.
- **H4:** Generalization is positively associated with pre-service teachers' RPCK.
- **H5:** Decomposition is positively associated with pre-service teachers' TPACK.

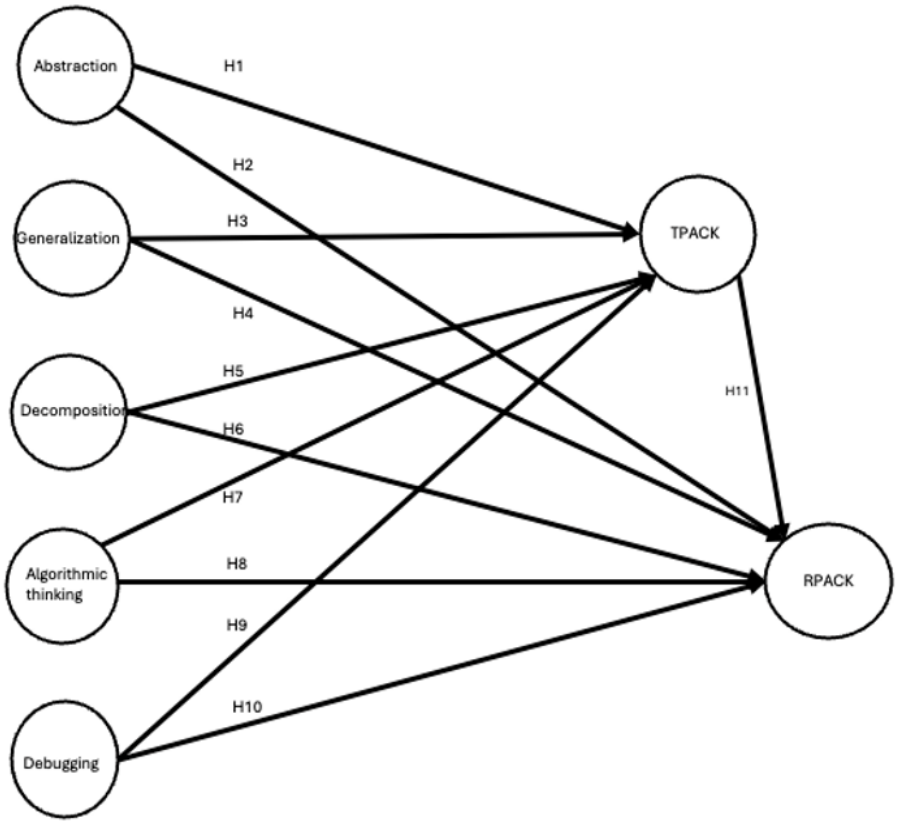


Figure 1. Hypothesized relationships among CT dimensions, TPACK, and RPCK (the authors' own elaboration from data)

- **H6:** Decomposition is positively associated with pre-service teachers' RPCK.
- **H7:** Algorithmic thinking is positively associated with pre-service teachers' TPACK.
- **H8:** Algorithmic thinking is positively associated with pre-service teachers' RPCK.
- **H9:** Debugging is positively associated with pre-service teachers' TPACK.
- **H10:** Debugging is positively associated with pre-service teachers' RPCK.
- **H11:** TPACK is positively associated with pre-service teachers' RPCK.

METHOD

Research Design and Procedure

This study employed an exploratory sequential mixed-methods design (Creswell et al., 2003), in which qualitative exploration preceded and informed the subsequent quantitative investigation. In the first phase, qualitative data were collected through open-ended questions to explore PESTs' perceptions of the competencies required for integrating robotics into teaching. The responses were systematically coded to identify recurring patterns and empirically emerging perceived competencies. Coding provides a structured process for organizing, categorizing, and thematically grouping qualitative data, enabling patterns and meanings to emerge from participants' responses (Williams & Moser, 2019). The analysis subsequently combined inductive, data-driven coding with deductive theoretical mapping, an approach that allows themes emerging from the data to be integrated with theoretically informed categories (Chandra & Shang, 2019; Fereday et al., 2006).

In the second phase, a quantitative cross-sectional survey was conducted to examine the relationships among CT, TPACK, and RPCK. Following the exploratory sequential mixed-methods design, findings from the qualitative phase informed the conceptualization and interpretation of the constructs examined in the survey.

A correlational survey design was employed to investigate the relationships among the study variables (Barker et al., 2015). The design step was adapted from Blair et al. (2013) with survey design, workshop, data collection, analysis and final report. The survey instrument was developed from a review of the literature and refined by qualitative findings collected during the workshop stage, which offered empirical support for the conceptualization of the CT, TPACK, and RPCK constructs. Prior to data collection, all participants signed an informed consent form after being informed about the objectives of the study, the voluntary nature of participation and the confidentiality of their responses. After the course on ER, participants were sent an online questionnaire.

Table 1. Demographic characteristics of participants across the qualitative and quantitative phases

Characteristic	Category	Qualitative phase (n = 128)		Quantitative phase (n = 150)	
		n	%	n	%
Gender	Female	113	88.3	129	86.0
	Male	15	11.7	21	14.0
Institution type	State university	64	50.0	72	48.0
	Private higher education institutions	64	50.0	78	52.0
Semester	Study semester range	3rd-7th	-	3rd-7th	-
Age (years)	M, SD, and range	M = 19.95, SD = 1.39, 17-25	-	M = 19.95, SD = 1.39, 17-25	-

Note. The qualitative sample consisted of participants who provided complete responses to the open-ended questionnaire, whereas the quantitative sample consisted of participants whose survey responses were included in the quantitative analysis

Participants

The participants were PESTs recruited from four higher education institutions in East Java, Indonesia. The institutions were purposively selected based on the criterion that they offered robotics courses or robotics-related learning activities within instructional media courses. The sample comprised two public and two private higher education institutions. This criterion ensured that the participating PESTs had relevant exposure to robotics-integrated learning in the context of instructional media. The characteristics of the participants are presented in **Table 1**.

The qualitative phase included 128 participants who provided complete responses to the open-ended questionnaire. For the quantitative phase, 152 responses were initially collected. Following a missing-data check, two incomplete responses were excluded, resulting in 150 complete cases included in the analysis. Across both phases, most participants were female (qualitative: 113, 88.3%; quantitative: 129, 86.0%), while male participants accounted for 11.7% and 14.0%, respectively. Participants were drawn from both public higher education institutions (qualitative: 50.0%; quantitative: 48.0%) and private higher education institutions (qualitative: 50.0%; quantitative: 52.0%). Participants were enrolled in the third through seventh semesters. The qualitative participants ranged in age from 17 to 25 years (mean [M] = 19.95, standard deviation [SD] = 1.39), and the quantitative participants had the same age range and descriptive statistics (M = 19.95, SD = 1.39). These age characteristics were calculated separately for each phase.

Before data collection, all participants completed a two-month ER course consisting of three standardized instructional sessions, with each session lasting approximately three hours. The course covered the fundamentals of ER, sensors, Arduino, programming, engineering design, and the integration of robotics into teaching and learning. Participants used the same instructional module, learning materials, project brief, robot type, learning objectives, and lesson plan across the participating institutions. The learning activities followed a project-based format in which participants worked collaboratively to design, assemble, program, test, and refine Arduino-based ER projects. The same instructional procedures and session duration were implemented across institutions, and instructors followed a common lesson plan to maintain consistency in course delivery. These standardization procedures ensured that participants across the four institutions received comparable learning experiences before completing the qualitative and quantitative research instruments.

Qualitative Data Collection

In the first phase, qualitative data were collected through an online open-ended questionnaire to explore pre-service teachers' perceptions of the perceived competencies developed through ER learning. The open-ended questions were developed by the research team based on the study objectives and informed by the literature on CT, TPACK, and robotics pedagogy to explore PESTs perceptions of competencies developed through ER learning. The questionnaire consisted of two open-ended questions: "Based on your experience in robotics learning, what perceived competencies, knowledge, and skills have you developed that you consider important for integrating robotics into teaching and learning? Please explain and provide examples." and "How can the competencies you gained through robotics learning help you solve problems, use technology, design learning activities, and integrate robotics with subject content such as science or STEM? Please explain based on your experience." The questionnaire was administered online. Before completing the questionnaire, participants were informed about the purpose of the study, the voluntary nature of their participation, and the confidentiality of their responses. Electronic informed consent was obtained from all participants prior to data collection.

Qualitative Data Analysis

The qualitative data were analyzed using a hybrid approach involving inductive coding followed by deductive theoretical mapping following Braun and Clarke (2006). The unit of analysis was any meaningful segment of a participant's response that revealed a competence relevant to integrated robotics learning. Through data familiarization, preliminary coding, code review and comparison, and the grouping of

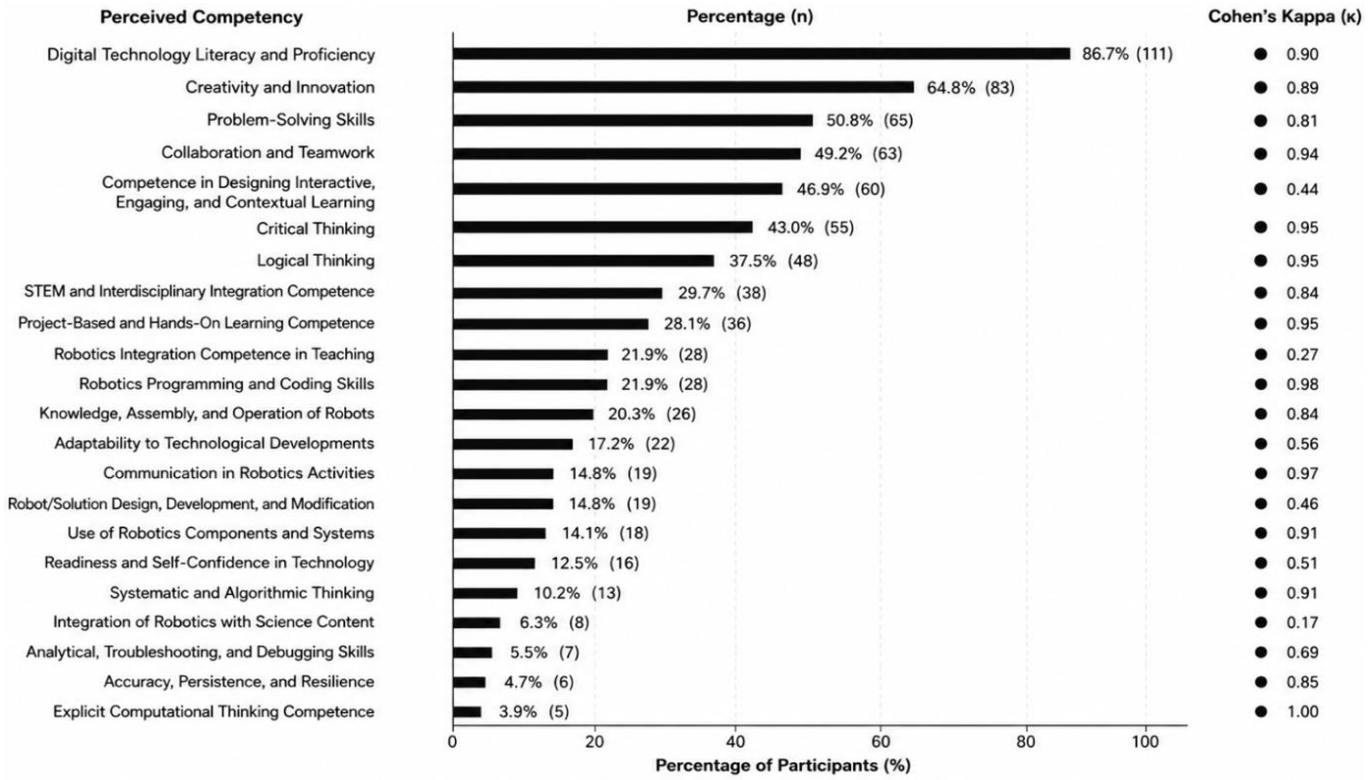


Figure 2. Percentage of perceived competencies required by pre-service teachers for integrating robotics into teaching (Percentages are based on the total number of participants [N = 128], with multiple coding permitted; Cohen's kappa indicates the level of agreement between two independent coders) (Excel output from data analysis)

conceptually similar codes into more general competency categories, the analysis was carried out inductively and data-driven. Two qualified coders from the study team examined and coded the replies using a predetermined coding process to improve the analysis's validity and consistency. Coding decisions and category assignments were compared, whilst discrepancies were discussed and resolved through consensus and peer checking amongst the authors. A single response may be assigned to more than one code if it contains more than one distinct competence. The coding structure was reviewed and refined iteratively, resulting in 22 empirically derived perceptual competencies. To assess inter-coder reliability, Cohen's kappa (κ) coefficients were calculated separately for each competency based on pre-consensus coding decisions made independently by both coders across all responses. The coefficients obtained ranged from 0.17 to 1.00, indicating varying levels of agreement across competencies. Based on the interpretation ranges used in this study, three competencies showed low agreement ($\kappa < 0.40$), four competencies showed moderate agreement (0.41-0.60), one competence showed substantial agreement (0.61-0.80), and 14 competences showed near-perfect agreement (0.81-1.00) (Landis & Koch, 1977). Cohen's kappa coefficients for the 22 competences are presented in **Figure 2**. These competences were then mapped deductively into the theoretical domains of CT, TPACK and RPCK. Competences not adequately represented by these three frameworks were retained as complementary and emergent competences. The frequency of occurrence of the competencies was used descriptively to illustrate their distribution amongst participants, rather than to assess their level of conceptual importance, in line with the principles of thematic analysis (Braun & Clarke, 2006).

The conceptual alignment between the qualitative competencies and quantitative constructs was used to contextualize the interpretation of the findings across the two phases. It was not intended to establish direct operational equivalence between individual qualitative competencies and questionnaire constructs. The questionnaire items were largely adapted from published measures, and the qualitative findings informed the interpretation of the selected quantitative constructs rather than serving as the sole basis for item development. Therefore, the quantitative phase examined selected self-reported dimensions of CT, TPACK, and RPCK; it did not constitute a quantitative validation of all 22 competencies identified in the qualitative phase.

Quantitative Data Collection and Instrument

The quantitative phase employed CT, TPACK, and RPCK instruments synthesized and adapted from established measures in the literature. Following the qualitative analysis, the derived empirically perceived competencies were mapped onto the theoretical domains of CT, TPACK, and RPCK based on their

conceptual characteristics. This mapping provided an empirical basis for interpreting and contextualizing the quantitative constructs examined in the subsequent phase, rather than serving as the sole basis for generating individual survey items. To assess PSTs' CT, questionnaire used the CT scale from W. Dong et al. (2024a) and C. Angeli et al. (2016) which is divided into five factors: abstraction (3 items), generalization (3 items), problem decomposition (3 items), algorithmic thinking (3 items), and debugging (3 items).

- Abstraction refers to identifying and retaining the essential characteristics of a problem while reducing unnecessary complexity (e.g., "I can identify the essential information needed to solve a problem when working with robotics").
- Generalization involves recognizing patterns and transferring previously developed solutions to similar or novel problems (e.g., "I can apply solutions from previous robotics problems to solve new problems with similar patterns").
- Problem decomposition refers to breaking complex problems into smaller, manageable components (e.g., "I can break down a complex robotics problem into smaller, manageable parts").
- Algorithmic thinking involves developing logical and systematic sequences of steps to reach a solution (e.g., "I can develop a logical sequence of steps to solve problems when working with robotics").
- Finally, debugging refers to identifying, evaluating, and correcting errors (e.g., "I can identify and correct errors when a robotics system or program does not work as expected").

A questionnaire also was developed using the TPACK and RPCK frameworks. The TPACK items were synthesized and adapted from Saritepeci (2022), D. Schmidt et al. (2009), and Angeli (2022) to assess pre-service teachers' ability to integrate TK with pedagogy and subject-matter content. In this study, TPACK focused on the pedagogically meaningful use of technology across three instructional processes:

- Planning TPACK refers to teachers' ability to design learning activities that effectively integrate technology, pedagogy, and subject content to achieve instructional objectives. Example item: "I can design learning activities that appropriately integrate technology with subject content."
- Implementation TPACK refers to teachers' ability to apply technology effectively during instruction to facilitate teaching and enhance student learning. Example item: "I can use technology to support effective teaching and student learning."
- Evaluation TPACK refers to teachers' ability to assess the effectiveness of technology integration in supporting learning processes and achieving instructional goals. Example item: "I can evaluate the effectiveness of technology integration in achieving learning objectives."

The TPACK items were initially organized into three instructional-process dimensions: planning (TPACK1-TPACK3), implementation (TPACK4-TPACK6), and evaluation (TPACK7-TPACK9). These dimensions were initially examined separately. However, the HTMT assessment yielded values exceeding .90, indicating insufficient discriminant validity among the three dimensions (Fornell & Larcker, 1981) . Consequently, the nine items were treated as a single TPACK construct in the final measurement model. This decision reflects both the empirical overlap among the dimensions and the study's conceptual focus on pre-service teachers' integrated competence in using technology to plan, implement, and evaluate elementary school science instruction.

In contrast, RPCK was conceptualized as a more robotics-specific form of PCK, focusing on PESTs' capacity to connect robotics knowledge with appropriate pedagogical strategies and disciplinary content, particularly in science learning. Following the item-level audit, two technically oriented indicators (RPCK1 and RPCK2) were removed because they primarily reflected robotics-related technical skills rather than the pedagogical integration of robotics with disciplinary content. The revised RPCK construct therefore comprised four items addressing the design of robotics-supported learning activities (2 items) and the use of robotics to facilitate students' understanding of disciplinary concepts (2 items) (C. Y. Hsu & Tsai, 2024). An example item is, "I can integrate robotics into appropriate teaching strategies to help students understand science concepts." Thus, while TPACK captures broader competence in the pedagogically meaningful integration of technology, RPCK focuses specifically on the pedagogical integration of robotics with disciplinary content.

All items were assessed using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree), as presented in **Appendix A**. The questionnaire items were adapted from previously published measures identified through a literature review, with the qualitative findings informing their selection, contextualization, and alignment with the competencies perceived by pre-service teachers. The items were adapted into Indonesian and tailored to the context of elementary school science teaching and ER. During the adaptation process, the authors also consulted subject-matter experts and academic colleagues to discuss the relevance, clarity, and appropriateness of the items for the intended research context. These consultations informed the refinement of the questionnaire before its use in the quantitative phase.

Quantitative Data Analysis

In addition, quantitative data from 150 PESTs were analyzed using PLS-SEM with SmartPLS 4. PLS-SEM was chosen because this study is exploratory in nature. This is because its aim is to develop and validate a new competency framework, rather than to test an established theory. This method is appropriate as it is prediction-oriented, capable of handling complex models, and can be used with small to medium-sized sample sizes (Hair et al., 2019). Based on these considerations, PLS-SEM was selected as the analytical method best suited to the research objectives. There were two phases of the analysis. Using outer loadings, Cronbach's alpha, composite reliability (CR), average variance extracted (AVE), and the heterotrait-monotrait (HTMT) ratio, the measuring model was first assessed for indicator reliability, internal consistency reliability, convergent validity, and discriminant validity. Second, path coefficients (β), t-statistics, p-values, and coefficients of determination (R^2) were used to evaluate the structural model. The statistical significance of the hypothesized structural relationships among CT, TPACK, and RPCK was assessed using a bootstrapping procedure with 5,000 subsamples. Finally, the qualitative and quantitative findings were integrated at the interpretation stage to examine how the empirically identified perceived competence corresponded with, complemented, or extended the structural relationships among CT, TPACK, and RPCK.

RESULTS

Qualitative Findings

Emergent perceived competencies identified from

The qualitative analysis identified 22 perceived competencies that PESTs considered relevant to robotics-integrated teaching (**Figure 2**). Overall, the distribution shows a clear dominance of broader technological, cognitive, pedagogical, and transversal competencies over highly technical robotics-specific skills. Digital technology literacy and proficiency was by far the most frequently perceived competency, mentioned by 86.7% of participants (n = 111), followed by creativity and innovation (64.8%, n = 83), problem-solving skills (50.8%, n = 65), collaboration and teamwork (49.2%, n = 63), and competence in designing interactive, engaging, and contextual learning (46.9%, n = 60). Cognitive competencies were also relatively prominent, particularly critical thinking (43.0%, n = 55) and logical thinking (37.5%, n = 48), while STEM and interdisciplinary integration (29.7%, n = 38) and project-based and hands-on learning (28.1%, n = 36) occupied a middle position in the distribution. By comparison, robotics-specific competencies were mentioned less frequently, with robotics integration competence in teaching and robotics programming and coding skills each reported by 21.9% of participants (n = 28), followed by knowledge, assembly, and operation of robots (20.3%, n = 26), adaptability to technological developments (17.2%, n = 22), and use of robotics components and systems (14.1%, n = 18). The least frequently identified competencies were integration of robotics with science content (6.3%, n = 8), analytical, troubleshooting, and debugging skills (5.5%, n = 7), accuracy, persistence, and resilience (4.7%, n = 6), and explicit computational thinking competence (3.9%, n = 5). Overall, the pattern suggests that PESTs' perceptions of robotics-integrated teaching competencies extend beyond technical knowledge of robotics and encompass broader technological literacy, creativity, problem-solving, collaboration, cognitive skills, and pedagogical design. The Cohen's kappa coefficients ranged from .17 to 1.00, indicating varying levels of intercoder agreement across competencies and providing an additional indication of the consistency of the coding process.

Theoretical mapping of the emergent perceived competencies

To further the descriptive identification of the 22 perceived competences, mapping was required. Theoretical mapping was carried out by comparing and grouping competences based on conceptual similarities within the CT, TPACK and RPCK frameworks. Competencies not fully covered by these three frameworks were retained in a separate domain, namely 'complementary and emergent competencies', without forcing them into existing theoretical categories. The mapping process resulted in four conceptual domains, as presented in **Table 2**, which form the theoretical basis for interpreting the competencies identified through qualitative data.

CT-related competencies

The findings revealed that robotics learning fostered several CT-related competencies, particularly logical thinking, problem-solving, analytical thinking, programming, and debugging. Participants described robotics activities as requiring logical reasoning and active solution seeking, as reflected by one participant: "We were encouraged to think logically, find solutions, and work collaboratively, which not only expanded our knowledge but also developed teamwork and creativity" (PST-03). Programming activities further involved iterative computational practices, as another participant stated, "Participants actively wrote, tested, and debugged code while facing challenges that required them to analyze problems, think logically, and find innovative solutions" (PST-29).

Although CT emerged as a conceptual domain, explicit references to the term 'CT' were relatively limited; participants more frequently described its constituent practices, including logical reasoning,

Table 2. Theoretical mapping of emergent perceived competencies into four conceptual domains

Conceptual domain	Codes	Empirically identified perceived competencies	Conceptual rationale
CT-related competencies	CRT-03	Problem-solving skills	Represents the cognitive and computational processes involved in robotics-related problem solving, including logical and systematic reasoning, algorithmic thinking, problem analysis, iterative testing, debugging, and solution refinement. These competencies indicate both explicit CT and computational practices associated with CT.
	CRT-06	CT	
	CRT-07	Logical thinking	
	CRT-18	Systematic and algorithmic thinking	
	CRT-20	Analytical, troubleshooting, and debugging skills	
	CRT-22	Explicit computational thinking competence	
TPACK-related competencies	CRT-01	Digital technology literacy and proficiency	Represents perceived competencies required to transform technological knowledge into pedagogically meaningful learning experiences. These perceived competencies connect technology proficiency with instructional design, experiential pedagogy, and the purposeful integration of technology into teaching and learning.
	CRT-05	Designing interactive, engaging, and contextual learning	
	CRT-09	Project-based and hands-on learning	
	CRT-10	Technology integration in teaching	
RPCK-related competencies	CRT-08	STEM and interdisciplinary integration	Represents robotics-specific knowledge and perceived competencies that support the pedagogical use of robotics, including programming, robot operation, components and systems, design and modification, and the integration of robotics with STEM and science content. Technical robotics competencies are interpreted as supporting knowledge for RPCK rather than as RPCK in isolation.
	CRT-11	Robotics programming and coding	
	CRT-12	Robot knowledge, assembly, and operation	
	CRT-15	Robot/solution design, development, and modification	
	CRT-16	Use of robotics components and systems	
	CRT-19	Integration of robotics with science content	
Complementary and emergent competencies	CRT-02	Creativity and innovation	Represents creative, social, adaptive, affective, and dispositional competencies that support robotics-integrated teaching but are not fully captured within the conceptual boundaries of CT, TPACK, or RPCK. Their emergence suggests that effective robotics integration requires broader competencies beyond cognitive, technological, pedagogical, and robotics-specific knowledge.
	CRT-04	Collaboration and teamwork	
	CRT-13	Adaptability to technological developments	
	CRT-14	Communication in robotics activities	
	CRT-17	Readiness and self-confidence in technology-enhanced teaching	
	CRT-21	Accuracy, persistence, and resilience	

Note. The mapping reflects the primary conceptual alignment of each empirically identified competency; Competencies with potential conceptual overlap were assigned to the domain that best represented their dominant meaning in participants' responses

problem-solving, programming, and debugging. Nevertheless, some participants explicitly recognized CT as an important outcome of robotics learning.

For example, one participant stated, "The robotics course improved our ability to understand and design systems, solve problems, and, most importantly, develop computational thinking" (PST-99). These findings indicate that CT was manifested both implicitly through computational practices and explicitly as a recognized competence associated with robotics learning.

TPACK-related competencies

The second conceptual domain comprised TPACK-related competencies, particularly digital technology literacy and proficiency, technology-integrated instructional design, and the ability to integrate emerging technologies into classroom practice. Participants generally emphasized technology in a broader educational sense rather than referring exclusively to robotics. For example, one participant highlighted the relationship between teachers' technological competence and the quality of the learning process: "If a teacher has mastered technology, the learning process will become more innovative and enjoyable. This can influence students' motivation to learn" (PEST-38). Another PST mention:

> "I believe this is highly important because, in an era of rapid technological advancement, teachers need to be innovative and creative, particularly in their use of technology. When teachers possess strong technological knowledge, they can create more innovative and engaging learning experiences, which can positively influence students' motivation to learn." (PEST-38)

These responses indicate that participants perceived technological competence not merely as the ability to operate technology, but as the capacity to use technology purposefully to transform teaching and learning. The

emphasis on technological understanding, instructional innovation, classroom integration, and responsiveness to students' learning needs conceptually aligns with TPACK-related competence. Importantly, these responses referred to technology in a general educational context, distinguishing this domain from RPCK-related competencies, which were characterized by more robotics-specific knowledge and its integration with pedagogy and disciplinary content.

RPCK-related competencies

The findings indicated that RPCK-related competencies extended beyond technical robotics knowledge to include its pedagogical integration with disciplinary content. One participant emphasized the role of robotics in STEM learning:

"Educational robotics is very important for the development of STEM learning in elementary schools. Through robotics, teachers can provide students with different, interactive, and enjoyable learning experiences, thereby increasing their engagement and understanding of abstract concepts in STEM." (PEST-33)

Participants also connected robotics-specific knowledge with its application in teaching. As one participant stated, "By participating in the robotics course, I was able to understand how sensors, actuators, and programming logic work and how they can be integrated into learning" (PEST-38). Together, these responses indicate that RPCK-related competencies involve connecting robotics-specific knowledge, pedagogical practices, and disciplinary content, enabling robotics to support meaningful and content-oriented learning experiences.

Complementary and emergent competencies

The findings also revealed complementary and emergent competencies extending beyond the core domains of CT, TPACK, and RPCK, particularly creativity, collaboration, communication, adaptability, self-confidence, and resilience. These competencies emerged as broader capacities developed through engagement in robotics activities. One participant emphasized the creative dimension of robotics, stating, "Robotics enhances creativity, particularly when designing the form, function, and movement of robots" (PEST-142). Another participant highlighted the social dimension, noting that "Robotics fosters collaboration and communication because participants typically work in groups and learn to cooperate" (PEST-93). These responses indicate that robotics learning develops competencies beyond TK and PK. Designing robots provides opportunities for creative expression and innovation, while collaborative robotics projects foster communication and teamwork.

Quantitative Findings

A total of 22 empirically identified competences were mapped into three theoretical domains, namely CT, TPACK, and RPCK. CT competences encompass problem-solving, logical and algorithmic thinking, and debugging. TPACK competences emphasize the meaningful integration of technology into learning, whilst RPCK encompasses specialized knowledge of robotics and its integration with pedagogy and learning materials. **Table 3** presents the mapping of competencies resulting from the qualitative analysis into theoretical domains, quantitative constructs, and the corresponding dimensions or indicators.

Table 3. Conceptual alignment between qualitatively identified competencies and quantitative constructs

Theoretical domain	Qualitative competency identified	Quantitative construct relation	Quantitative indicator
CT	Problem-solving skills	CT – Decomposition	Breaking a complex problem into smaller, manageable components
	Critical thinking	CT – Abstraction	Identifying essential information and simplifying complex problems
	Logical thinking	CT – Algorithmic thinking	Developing logical and sequential solution procedures
	Systematic and algorithmic thinking	CT – Algorithmic thinking	Formulating step-by-step procedures for solving problems
	Analytical, troubleshooting, and debugging skills	CT – Debugging	Identifying, testing, and correcting errors
	Explicit CT competence	CT – General CT orientation	Recognizing and applying computational thinking practices
TPACK	Digital technology literacy and proficiency	TPACK	Meaningful use of technology for teaching and learning
	Designing interactive, engaging, and contextual learning	TPACK – Planning	Designing technology-integrated learning activities
	Project-based and hands-on learning	TPACK – Implementation	Implementing technology-supported active learning

Table 3 (Continued).

Theoretical domain	Qualitative competency identified	Quantitative construct relation	Quantitative indicator
	Technology integration in teaching	TPACK – Planning, implementation, and evaluation	Integrating technology with pedagogy and content
RPCK	STEM and interdisciplinary integration	RPCK	Integrating robotics with STEM and disciplinary content
	Robotics programming and coding	RPCK	Applying robotics-related knowledge to support instruction
	Robot knowledge, assembly, and operation	RPCK	Using robotics knowledge and operation in teaching
	Robot/solution design, development, and modification	RPCK	Designing and modifying robotics-supported learning activities
	Use of robotics components and systems	RPCK	Applying robotics components and systems for instruction
	Integration of robotics with science content	RPCK	Using robotics to support science-content learning
Complementary and emergent competencies	Creativity and innovation	-	Qualitative finding; not measured as a separate quantitative construct
	Collaboration and teamwork	-	Qualitative finding; not measured as a separate quantitative construct
	Adaptability to technological developments	-	Qualitative finding; not measured as a separate quantitative construct
	Communication in robotics activities	-	Qualitative finding; not measured as a separate quantitative construct
	Readiness and self-confidence in technology-enhanced teaching	-	Qualitative finding; not measured as a separate quantitative construct
	Accuracy, persistence, and resilience	-	Qualitative finding; not measured as a separate quantitative construct

This mapping serves as the empirical basis for interpreting the quantitative constructs, whilst the quantitative instruments were developed primarily through the synthesis and adaptation of instruments already available in the literature. Based on this conceptual alignment and the theoretical relationships described in the literature, the quantitative stage tests the hypothesized relationships between the five dimensions of CT (abstraction, generalization, decomposition, algorithmic thinking, and debugging), as well as TPACK and RPCK.

Building on this conceptual alignment and the theoretical relationships established in the literature, the quantitative phase examined the hypothesized relationships among the five CT dimensions (abstraction, generalization, decomposition, algorithmic thinking, and debugging), TPACK, and RPCK.

Construct reliability and validity

Using PLS-SEM, the measurement model was first assessed to establish the reliability and validity of the constructs before evaluating the hypothesized structural relationships. As presented in **Table 4**, the assessment included descriptive statistics, factor loadings, Cronbach's alpha coefficients, CR, and AVE.

Table 4. Descriptive statistics, loading factor, Cronbach's alpha, CR, AVE, and rho_A of the robotic TPACK and CT indicators

Indicator	M	SD	Loading factor	AVE	Cronbach's alpha	CR	rho_A
CT	3.58	.69					
Abstraction	3.77	.64		.79	.86	.92	.87
Abstraction1	3.77	.68	.89				
Abstraction2	3.75	.62	.92				
Abstraction3	3.79	.64	.85				
Generalization	3.63	.67		.74	.82	.89	.83
Generalization1	3.65	.68	.86				
Generalization2	3.59	.67	.83				
Generalization3	3.64	.66	.88				
Decomposition	3.45	.71		.81	.88	.93	.89
Decomposition1	3.45	.73	.90				

Table 4 (Continued).

Indicator	M	SD	Loading factor	AVE	Cronbach's alpha	CR	rho_A
Decomposition2	3.45	.67	.89				
Decomposition3	3.45	.73	.91				
Algorithmic thinking	3.53	.69		.75	.83	.90	.83
Algorithmic thinking 1	3.57	.65	.86				
Algorithmic thinking 2	3.52	.71	.86				
Algorithmic thinking 3	3.49	.70	.87				
Debugging	3.52	.68		.79	.87	.92	.87
Debugging1	3.52	.67	.88				
Debugging2	3.47	.66	.89				
Debugging3	3.57	.70	.90				
RPCK	3.57	.72		.67	.90	.92	.91
RPCK1	3.78	.71	.80				
RPCK2	3.43	.78	.82				
RPCK3	3.58	.71	.84				
RPCK4	3.58	.69	.88				
RPCK5	3.52	.70	.90				
RPCK6	3.52	.67	.90				
TPACK	3.74	.69		.63	.93	.94	.93
TPACK1	3.70	.70	.83				
TPACK2	3.66	.73	.87				
TPACK3	3.84	.71	.85				
TPACK4	3.62	.67	.85				
TPACK5	3.70	.71	.87				
TPACK6	3.65	.63	.87				
TPACK7	3.90	.67	.86				
TPACK8	3.81	.72	.86				
TPACK9	3.81	.64	.84				

Table 5. Correlation and discriminant validity of Fornell-Larcker criterion

Latent variable	1	2	3	4	5	6	7
Abstraction	.89						
Algorithmic thinking	.59***	.86					
Debugging	.66***	.68***	.89				
Decomposition	.58***	.74***	.66***	.90			
Generalization	.83***	.68***	.67***	.66***	.86		
RPCK	.69***	.59***	.68***	.69***	.73***	.82	
TPACK	.61***	.62***	.60***	.57***	.67***	.73***	.79

Note. ***p < .001; **p < .01; *p < .05

Abstraction (M = 3.77, SD =.64), generalization (M = 3.63, SD =.67), decomposition (M = 3.45, SD =.71), algorithmic thinking (M = 3.53, SD =.69) and debugging (M = 3.52, SD =.68) were the five first-order indicators that made up the CT construct. Each of these indicators was measured with three items, with an overall CT mean of 3.58 (SD =.69). Abstraction was rated the highest, debugging the lowest. Thus, the PESTs felt more confident in explaining the concepts of sensor-based robotics than in locating and correcting errors in the programming of robots. The average score for the six-item RPCK construct was 3.57 (SD = 72), and the average score for the nine-item TPACK construct, which addressed the planning, implementation, and assessment of technology-integrated science instruction, was 3.74 (SD =.69).

The measurement model demonstrated satisfactory convergent validity and internal consistency reliability. All retained items showed standardized outer loadings ranging from .80 to .92, exceeding the recommended threshold of .70 (Hulland, 1999). While AVE values ranged from .63 to .81, surpassing the minimum criterion of .50 (Fornell & Larcker, 1981). Reliability was also confirmed, with CR (.89 to .94), rho_A (.83 to .93), and Cronbach's alpha (.82 to .93) all exceeding the recommended threshold of .70 (Hair et al., 2017; Nunnally & Bernstein, 1994). Collectively, these results indicate that the measurement model possesses adequate convergent validity and internal consistency, supporting its use for subsequent structural model analysis.

Discriminant validity

It used the Fornell-Larcker criterion and the HTMT ratio to assess discriminant validity. The reports are shown in **Table 5** and **Table 6**.

Table 6. HTMT ratio of CT, TPACK, and RPCK

Dimensions	1	2	3	4	5	6	7
Abstraction							
Algorithmic thinking	.70						
Debugging	.76	.80					
Decomposition	.67	.86	.75				
Generalization	**.99**	.82	.79	.77			
RPCK	.79	.67	.77	.77	.85		
TPACK	.68	.69	.66	.61	.77	.79	

Table 7. Bootstrapped structural path coefficients of the refined CT-TPACK-RPCK model

Hypotheses	Association	b	M	SD	t	p	Decision
H1	Abstraction→TPACK	.29	.30	.09	3.13	< .00	Supported
H2	Abstraction→RPCK	.13	.12	.10	1.27	.20	Not supported
H3	Generalization→TPACK	-	-	-	-	-	Excluded from analysis
H4	Generalization→RPCK	-	-	-	-	-	Excluded from analysis
H5	Decomposition→TPACK	.10	.09	.11	.88	.38	Not Supported
H6	Decomposition→RPCK	.34	.33	.10	3.58	< .00	Supported
H7	Algorithmic thinking→TPACK	.26	.26	.10	2.65	.01	Supported
H8	Algorithmic thinking→RPCK	-.12	-.11	.11	1.15	.25	Not supported
H9	Debugging→TPACK	.17	.16	.12	1.41	.16	Not supported
H10	Debugging→RPCK	.23	.23	.10	2.24	.03	Supported
H11	TPACK→RPCK	.39	.39	.08	4.58	< .00	Supported

Note. β: Standardized path coefficient; t: Bootstrapping t-value; p: Significance level; **H3** and **H4** were excluded from the structural analysis because the generalization construct was not retained due to high empirical overlap with abstraction (HTMT = .99); Supported hypotheses indicate statistically significant positive associations, whereas not supported hypotheses indicate non-significant associations

All inter-construct correlations in **Table 5** were statistically significant at $p < .001$ and ranged from $r = .57$ (decomposition→TPACK) to $r = .83$ (generalization→abstraction). The square root of the AVE for all the constructs (from .79 to .90) is greater than all the correlations between constructs, which means that each construct explains more variance from its own indicators than variance shared with other constructs in the model by Fornell and Larcker (1981) criterion. **Table 6** shows that all of the HTMT ratios are below the conservative threshold of .90. However, the HTMT results in **Table 6** indicated that the HTMT value between generalization and abstraction was .99. The remaining HTMT values ranged from .61 to .86, indicating adequate discriminant validity among the other constructs. Given the high conceptual and empirical overlap between generalization and abstraction, generalization was not retained in the subsequent structural analysis.

CT, TPACK, and RPCK relationship

Table 7 illustrates corresponding bootstrapped β for the hypothesized relationships in the refined model of relationship between CT, TPACK, and RPC. Generalization-related hypotheses (**H3** and **H4**) were excluded from the structural analysis because the Generalization construct was not retained due to its high empirical overlap with abstraction. Among the remaining hypotheses, five relationships were supported. Abstraction was positively associated with TPACK (**H1**: $\beta = .29$, $p < .001$), but its association with RPCK was not significant (**H2**: $\beta = .13$, $p = .20$). Decomposition was not significantly associated with TPACK (**H5**: $\beta = .10$, $p = .38$) but was positively associated with RPCK (**H6**: $\beta = .34$, $p < .001$). Algorithmic thinking was positively associated with TPACK (**H7**: $\beta = .26$, $p = .01$), whereas its association with RPCK was not significant (**H8**: $\beta = -.12$, $p = .25$). Similarly, debugging was not significantly associated with TPACK (**H9**: $\beta = .17$, $p = .16$) but was positively associated with RPCK (**H10**: $\beta = .23$, $p = .03$). Finally, TPACK was positively associated with RPCK (**H11**: $\beta = .39$, $p < .001$).

The findings indicate that different CT dimensions showed distinct patterns of association with TPACK and RPCK. Abstraction and algorithmic thinking were significantly associated with TPACK, whereas decomposition and debugging were significantly associated with RPCK. Among the CT dimensions, abstraction showed the strongest association with TPACK ($\beta = .29$), while decomposition showed the strongest association with RPCK ($\beta = .34$). The strongest relationship in the overall model was between TPACK and RPCK ($\beta = .39$). These findings suggest that CT dimensions do not contribute uniformly across pedagogical domains; rather, their associations vary according to whether the target competency concerns general technology integration (TPACK) or robotics-specific pedagogical knowledge (RPCK). This finding highlights the distinctive roles of individual CT dimensions in supporting technology-enhanced science teaching among PESTs.

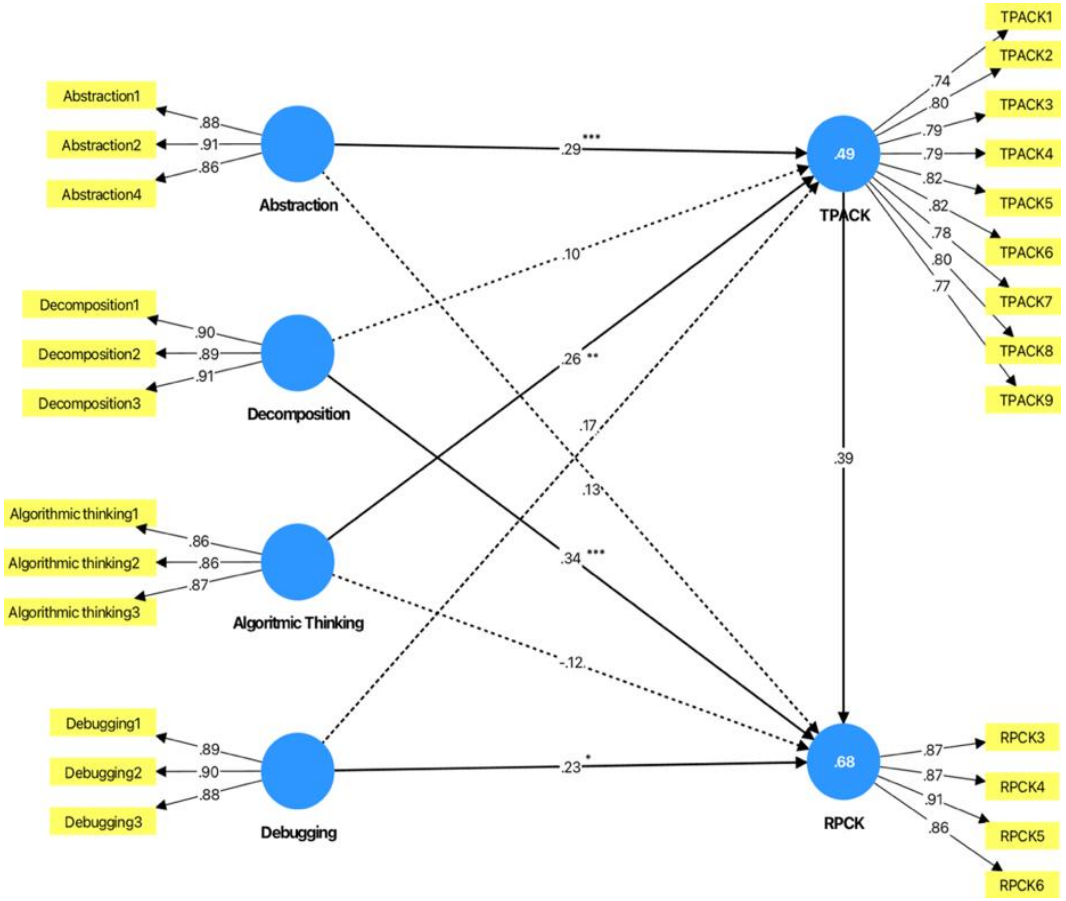


Figure 3. Model of PLS-SEM CT against TPACK and RPACK (***p < .001; **p < .01; *p < .05) (Smart PLS app output)

Figure 3 illustrates the relationships between CT, TPACK, and RPCK, while **Table 7** presents the corresponding bootstrapped β for the hypothesized relationships in the refined model. Generalization-related hypotheses (**H3** and **H4**) were excluded from the structural analysis because the Generalization construct was not retained due to its high empirical overlap with abstraction. Among the remaining hypotheses, five relationships were supported. Abstraction was positively associated with TPACK (**H1**: β = .29, p < .001), but its association with RPCK was not significant (**H2**: β = .13, p = .20). Decomposition was not significantly associated with TPACK (**H5**: β = .10, p = .38) but was positively associated with RPCK (**H6**: β = .34, p < .001).

Algorithmic thinking was positively associated with TPACK (**H7**: β = .26, p = .01), whereas its association with RPCK was not significant (**H8**: β = -.12, p = .25). Similarly, debugging was not significantly associated with TPACK (**H9**: β = .17, p = .16) but was positively associated with RPCK (**H10**: β = .23, p = .03). Finally, TPACK was positively associated with RPCK (**H11**: β = .39, p < .001).

Structural model assessment

Figure 4 illustrates the final refined PLS-SEM model examining the associations among CT dimensions, TPACK, and RPCK. The bootstrapping results indicated five statistically significant positive relationships. Abstraction (β = .38, t = 4.61, p < .001) and algorithmic thinking (β = .39, t = 5.26, p < .001) were positively associated with TPACK, with algorithmic thinking showing a slightly stronger association. Decomposition (β = .30, t = 4.16, p < .001) and debugging (β = .24, t = 2.90, p < .01) were positively associated with RPCK. TPACK was also positively associated with RPCK (β = .42, t = 5.70, p < .001), representing the strongest relationship in the model. The model explained 47% of the variance in TPACK (R^2 = .47) and 68% of the variance in RPCK (R^2 = .68). These findings indicate distinct patterns of association between CT dimensions and PK: abstraction and algorithmic thinking were associated with TPACK, whereas decomposition and debugging were associated with RPCK. Given the exploratory refinement of the model, these relationships should be interpreted as associations rather than causal effects.

Table 8 summarizes the assessment of the refined structural model. The reported inner VIF values ranged from 1.57 to 2.45, below the threshold of 3.00, indicating no substantial collinearity concerns for the reported relationships. Effect sizes (f^2) ranged from .09 to .33, with TPACK showing the largest f^2 in relation to RPCK (f^2 = .33), followed by abstraction and algorithmic thinking in relation to TPACK (both f^2 = .18). Regarding model fit, the SRMR values for the saturated and estimated models were both .07, below the commonly used threshold of

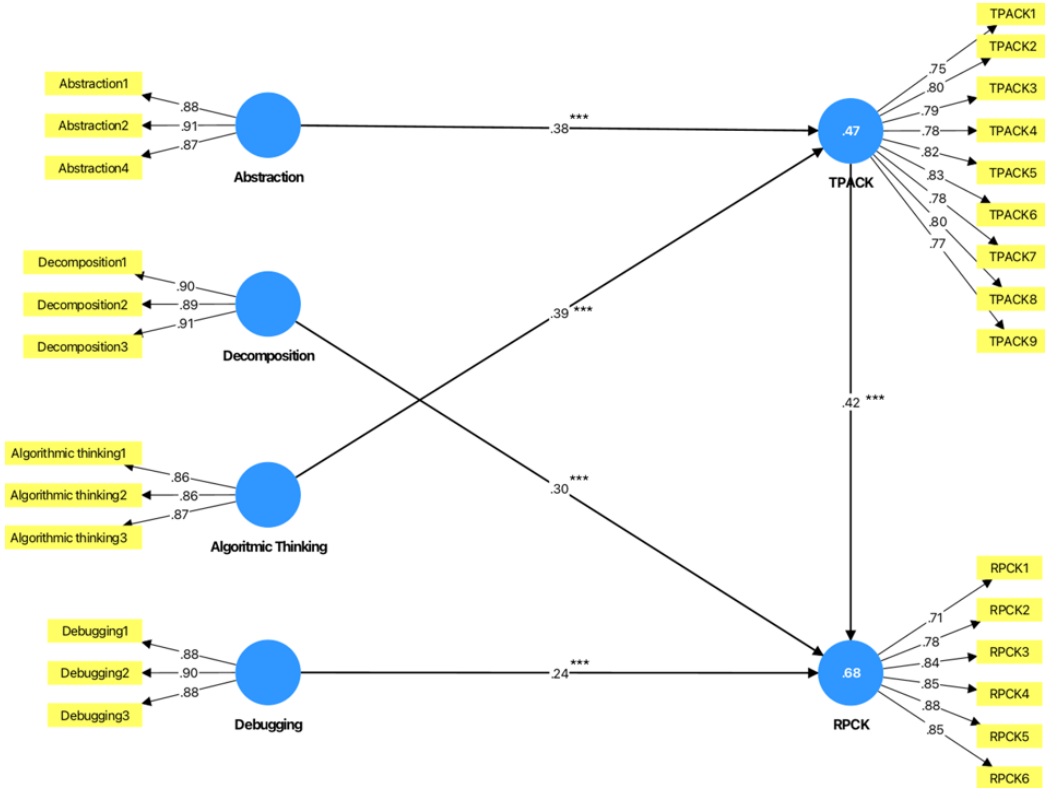


Figure 4. Final refined PLS-SEM model of CT, TPACK, and RPCK (Standardized path coefficients (β) are displayed on the structural paths, and coefficients of determination R^2 are shown within the endogenous constructs; Values adjacent to measurement indicators represent standardized outer loadings; ***p < .001; **p < .01; *p < .05) (Smart PLS app output)

Table 8. Structural model assessment

Assessment	Relationships	Values	Cutoff/interpretation	Reference
Collinearity (inner VIF)	Abstraction → TPACK	1.57	≤ 3.00: no collinearity concern	Hair et al. (2019)
	Decomposition → RPCK	1.92		
	Algorithmic thinking → TPACK	1.57		
	Debugging → RPCK	2.45		
	TPACK → RPCK	1.69		
f^2	Abstraction → TPACK	.18	.02 = small; .15 = medium; .35 = large; < .02 = negligible	Cohen (1988); Hair et al. (2019)
	Decomposition → RPCK	.15		
	Algorithmic thinking → TPACK	.18		
	Debugging → RPACK	.09		
	TPACK → RPCK	.33		
Explained variance (R^2)	TPACK	.47	.25 = weak; .50 = moderate; .75 = substantial	Hair et al. (2019)
	RPCK	.68		
Model fit	SRMR (saturated; estimated)	.07; .07	Both below the commonly used .08 threshold	Hair et al. (2019)
	d_ULS (saturated)	1.81	Exceeds the 99% bootstrap reference (1.49)	Hair et al. (2019)
	d_G (saturated)	1.24	Approximately equal to the 95% reference (1.24); below the 99% reference (1.41)	Hair et al. (2019)
	χ^2 (saturated; estimated)	975.74; 983.59	Reported model-fit statistic	Hair et al. (2019)
	NFI (saturated; estimated)	.73;72	Below the commonly used .90 reference	Hair et al. (2019)

Note. VIF: Variance inflation factor; SRMR: Standardized root mean square residual; d_ULS: Unweighted least squares discrepancy; d_G: Geodesic discrepancy; NFI: Normed fit index

.08. However, the bootstrap-based discrepancy assessments provided mixed evidence. For the saturated model, d_ULS = 1.81 exceeded the 99% bootstrap reference value of 1.49, whereas d_G = 1.24 was approximately equal to the 95% reference value of 1.24 and below the 99% reference value of 1.41. The NFI values were .73 for the saturated model and .72 for the estimated model, both below the commonly used reference value of .90.

Overall, the model showed no substantial collinearity concerns, while the model-fit indicators provided mixed evidence and warrant cautious interpretation.

DISCUSSION

This study provides an empirically informed mapping of perceived competencies for robotics-integrated teaching among PESTs. The qualitative phase identified 22 perceived competencies from participants' responses, which were subsequently organized into four domains: CT, TPACK, RPCK, and complementary and emergent professional competencies.

The findings extend understanding of ER by indicating that PESTs perceive effective robotics-integrated teaching as involving cognitive, pedagogical, technological, and professional competencies rather than TK alone (C. Y. Hsu & Tsai, 2024; Mishra & Koehler, 2006). This perspective suggests that robotics teaching extends beyond operating robotic devices or teaching programming. Instead, participants emphasized the use of robotics to create meaningful learning experiences that support scientific inquiry, CT, collaboration, and problem-solving (Angeli, 2022; S.-C. Kong et al., 2023; Scaradozzi et al., 2019). Therefore, ER can be viewed as a pedagogical tool for facilitating learning rather than as an instructional objective in itself, consistent with constructionist learning theory, which emphasizes learning through designing, building, and reflecting on meaningful artifacts (Papert, 1993, 2020). The structural model further demonstrates that CT provides the cognitive foundation for robotics-integrated teaching, while TPACK was positively associated with RPCK. In particular, abstraction and algorithmic thinking were associated with TPACK, while decomposition, and debugging showed significant association to RPCK, indicating that computational reasoning is essential for designing and implementing robotics-supported learning and technology (Wing, 2006). Then, methodologically, this study also contributes by applying an exploratory sequential mixed-methods design to identify PESTs' perceived competencies empirically before examining associations among the constructs. This approach complements existing TPACK and RPCK models, which have largely been developed from theoretical perspectives, by providing evidence grounded in pre-service teachers' authentic experiences (Creswell & Plano Clark, 2018; Rodrigues et al., 2024).

The qualitative findings reveal that pre-service teachers perceived robotics-integrated teaching as extending beyond robotics-specific knowledge. Digital technology literacy emerged as the most frequently identified competency, followed by creativity, problem-solving, collaboration, and the ability to design interactive learning. This pattern suggests that pre-service teachers view ER as a pedagogical approach that promotes meaningful learning rather than merely teaching robotics or programming. Interestingly, robotics-specific competencies, such as programming, robot assembly, and knowledge of robotics components, were identified less frequently than broader pedagogical and professional competencies. This finding indicates that pre-service teachers place greater emphasis on using robotics to facilitate student learning than on mastering robotics technology itself. This perspective aligns with recent studies showing that ER promotes higher-order thinking, collaboration, creativity, and authentic problem-solving when integrated into meaningful learning (Haddadin, 2024; Isnaini et al., 2019; Puzio, 2025). It also supports the argument that preparing teachers for robotics-integrated instruction requires a broad set of professional competencies, including communication, collaboration, creativity, and instructional design, to create engaging STEM learning environments. These findings therefore suggest that teacher education programs should prioritize pedagogical and professional competence alongside robotics-specific skills to prepare future teachers for authentic robotics-integrated science instruction.

The quantitative findings demonstrated distinct patterns of association among the CT dimensions, TPACK, and RPCK. Abstraction was positively associated with TPACK, suggesting that the ability to identify essential features and simplify complex information may be particularly relevant to pre-service teachers' perceived competence in designing, implementing, and evaluating technology-supported science instruction. Abstraction is a core cognitive process of CT because it enables individuals to reduce complexity and focus on essential features when solving problems (Grover & Pea, 2013). Algorithmic thinking was also positively associated with TPACK, suggesting that the ability to develop logical and sequential solutions may be particularly relevant to instructional planning and technology integration. Kong and Lai (2022) argued that algorithmic thinking should be embedded within teachers' TK, while Saritepeci (2022) also highlighted its contribution to instructional decision-making in technology-rich classrooms. From a constructionist perspective, designing, testing, and refining programs can develop procedural thinking through active engagement with computational artifacts (Papert & Harel, 2002). The dimensions are related to planning and less related to specific technology applications. Both dimensions are related to the general TPACK construct and less related to the construct of robotics pedagogy. These relationships may be why neither dimension was strongly related to RPCK.

In addition, the high HTMT value between abstraction and generalization (.99) raises questions about the empirical distinctiveness of these two CT dimensions in the present context. Although abstraction involves identifying essential information and simplifying complex problems, generalization concerns recognizing patterns and applying previously learned solutions to new problems. The contextualization of both dimensions around robotics-related problem-solving may have contributed to their overlap, particularly

because identifying relevant information and applying prior solutions can occur within the same robotics activity. However, the present findings do not establish that the robotics context caused this overlap. Generalization was therefore excluded from the subsequent structural analysis because its discriminant validity with abstraction was insufficient. This decision narrowed the scope of the refined model, which consequently examined associations involving the retained CT dimensions rather than the full set of initially specified CT dimensions. The resulting model should be interpreted as an exploratory refinement informed by the measurement-model assessment, not as a full confirmation of the original hypothesized model. Future studies should examine whether revised item wording and additional evidence from content validation can better distinguish abstraction from generalization in ER settings.

Decomposition and debugging were also positively associated with RPCK. These perceived competencies reflect the specialized pedagogical demands of robotics-integrated teaching. Decomposition may enable teachers to organize complex robotics tasks into manageable learning activities, while debugging may support teachers in identifying and correcting programming errors during robotics instruction. Both perceived competencies may help teachers manage the technical complexity of robotics-based learning and facilitate students' iterative problem-solving processes (W. Wang & Shen, 2026). This result agrees with the findings of S. Yang et al. (2024), who reported that debugging skills are among those acquired through ER. No significant relationships were found between TPACK and either construct. TPACK involves knowledge of more than one technology and subject area. Skills learned in one technological area may show weaker connections to TPACK. Connections between TPACK and proactive instructional design skills involving technology use for teaching and learning are likely to be stronger than connections between TPACK and debugging skills.

Although TPACK showed the strongest association with RPCK among the predictors included in the model, the significant associations of decomposition and debugging with RPCK indicate that robotics-specific CT dimensions remain relevant alongside broader technology-integration competence. Decomposition showed a stronger association with RPCK than debugging, suggesting that the ability to analyze and organize complex robotics tasks may be particularly relevant to perceived robotics pedagogical competence. These findings support the view that effective robotics-integrated teaching involves both broad pedagogical technology knowledge and domain-specific cognitive competencies developed through engagement with robotics activities (H. Wang et al., 2024). Debugging skills were less strongly linked to RPCK than decomposition skills, perhaps because debugging skills apply to classroom problems related to teaching robotics, whereas decomposition skills are more general teaching skills. Teacher education programs may want to incorporate instruction on how to use decomposition and debugging skills when teaching robotics and other technology topics (W. Dong et al., 2024). Some limitations of the current study, such as its cross-sectional design and reliance on self-report data for all measures, should be noted. Further study is needed on the extent to which TPACK mediates other relationships between algorithmic and abstract thinking skills and RPCK.

In addition to competencies measured in the current study (CT, TPACK, and RPCK) qualitative findings include other competencies that may be important for science teachers using robotics: creativity, collaboration, communication, adaptability, self-confidence, persistence, and resilience (W. Dong et al., 2024). Other competencies may be useful for collaboration and other tasks involved in robotics teaching, but they were not measured in the current study. Other studies support the findings related to other competencies, including the role of creativity in robotics education (Y. Yang et al., 2020) and other factors, including resilience, in pre-service teachers' collaboration during programming tasks (Kim et al., 2024). Other methods were not used in the current study to measure the other competencies discussed here, so their relationships with other competencies are unclear. The other competencies identified in the current study add to our knowledge of competencies related to robotics education but are not fully developed. Further research on other competencies related to robotics teacher education is needed.

This study has several limitations. First, the cross-sectional design captured pre-service teachers' perceived competencies at a single point in time; therefore, the findings cannot explain how CT, TPACK, and RPCK develop throughout teacher education or during teaching practice. In addition, common-method bias was not statistically assessed; therefore, its potential influence on the observed associations among these constructs cannot be ruled out. Future research should employ longitudinal or intervention-based designs to examine changes in these competencies over time. Second, both the qualitative and quantitative findings were based primarily on self-reported data. Although this approach provides valuable insights into participants' perceived competencies, it may not fully reflect their demonstrated teaching practices. Future studies should incorporate classroom observations, teaching performance assessments, or teaching portfolios to examine the extent to which perceived competencies correspond to demonstrated competence, consistent with the distinction between perceived and demonstrated competence highlighted by Gonscherowski and Rott (2025). Third, the competency

mapping was developed from PESTs in Indonesia, and its applicability to other educational levels, in-service teachers, or different cultural and educational contexts remains uncertain. Future studies should therefore examine the mapping across diverse teacher populations and educational systems. This consideration is particularly relevant given recent empirical evidence highlighting the need for context-specific TPACK instruments in primary mathematics and science education, where theoretical subdomains may overlap in self-reported evaluations (Ahmichane et al., 2025).

Another limitation concerns the scope of the quantitative phase. Although the qualitative phase identified 22 perceived competencies, only the CT, TPACK, and RPCK domains were examined quantitatively, whereas the complementary and emergent domain was derived solely from the qualitative findings and was not quantitatively examined. Future research should investigate this domain empirically and examine its relationships with the other competency domains. In addition, the present study focused on mapping perceived competencies and examining associations among the selected constructs rather than evaluating the effectiveness of the mapping for improving robotics-integrated teaching. Experimental or intervention-based studies are therefore needed to examine whether targeted development of these competencies is associated with changes in teachers' instructional practices and students' learning outcomes. Finally, although pre-service teachers described several practices related to CT in the qualitative phase, they rarely used the explicit term "computational thinking." This may suggest that participants engaged in CT-related practices without fully recognizing or articulating them within the CT conceptual framework. Future research should therefore investigate whether targeted teacher education can be relevant to pre-service teachers' explicit awareness of CT and support their ability to intentionally identify, integrate, and teach CT through ER.

CONCLUSION

This study presents an empirically grounded view on the competencies required for robotics-integrated teaching as perceived in elementary teacher education. The results, which combine inductive qualitative inquiry with quantitative model validation, suggest that the preparation of future teachers for ER includes cognitive, pedagogical, technological and professional perceived competencies based on the self-reported experiences of the participants. The resultant framework provides a structured and empirically-grounded frame of reference for teacher education curricula, professional development and perceived competency assessment. For example, in a course such as ER for Elementary Teachers, an instructor could take the four competency domains as concrete design targets, having pre-service teachers decompose a robot navigation task before programming (cognitive), come up with formative assessment questions for the activity (pedagogical), debug programming errors on their own (technological), and think about modifying the task for students with different levels of technological access (professional). In doing so, the framework can serve university instructors as a practical rubric for designing lessons and assessing competencies, rather than merely a theoretical reference. Teacher education institutions are encouraged to integrate robotics learning into authentic pedagogical experiences, and future research should validate the framework in diverse contexts using objective, performance-based measures, as well as self-report data.

Author contributions: MAT: conceptualization, methodology, resources, writing – original draft; **NI:** data curation, methodology; **AHRI:** formal analysis, visualization; **AWK:** formal analysis, writing – original draft, writing – review & editing; **WW:** supervision, writing – review & editing. All authors agreed with the results and conclusions.

Funding: This study was funded by Jatim Melaju Malang State University.

Acknowledgments: The authors would like to thank Malang State University and the Government of East Java Province, Indonesia, for approving and supporting this study through research funding under contract no. 21.4.42/UN32.14.1/LT/2026. The authors would also like to thank all respondents for their participation and valuable contributions to this study.

Ethical statement: This study was conducted in accordance with the ethical principles and research guidelines established by Universitas Negeri Malang, as outlined in PPKI UM, 2017 edition. The research procedures were implemented in accordance with the applicable institutional guidelines to ensure responsible research conduct and the appropriate treatment of participants.

AI statement: ChatGPT (OpenAI) was used during manuscript preparation to support language refinement, including grammar checking and improving sentence clarity. All suggested revisions were subsequently evaluated and edited by the authors to ensure that they accurately reflected the intended meaning. The authors retain full responsibility for the manuscript and its scholarly content. No AI-based tools were used to produce the research data, perform the statistical analyses, or establish the study's findings.

Declaration of interest: No conflict of interest is declared by the authors.

Data sharing statement: Data supporting the findings and conclusions are available upon request from the corresponding author.

REFERENCES

Ahmichane, J., Jhilal, A., Hadder, Y., & El Mallahi, M. (2025). Validating a TPACK instrument in the Moroccan context: A four-factor model for preservice mathematics and sciences teachers. *International Journal of Environment, Engineering and Education, 7*(2), 158-167. https://doi.org/10.55151/ijeedu.v7i2.294

Alam, A., & Mohanty, A. (2024). Integrated constructive robotics in education (ICRE) model: A paradigmatic framework for transformative learning in educational ecosystem. *Cogent Education, 11*(1), Article 232487. https://doi.org/10.1080/2331186X.2024.2324487

Angeli, C. (2022). The effects of scaffolded programming scripts on pre-service teachers' computational thinking: Developing algorithmic thinking through programming robots. *International Journal of Child-Computer Interaction, 31*, Article 100329. https://doi.org/10.1016/j.ijcci.2021.100329

Angeli, C., & Jaipal-Jamani, K. (2018). Preparing pre-service teachers to promote computational thinking in school classrooms. In M. Khine (Ed.), *Computational thinking in the STEM disciplines* (pp. 127-150). Springer. https://doi.org/10.1007/978-3-319-93566-9_7

Angeli, C., & Valanides, N. (2013). Technology mapping: An approach for developing technological pedagogical content knowledge. *Journal of Educational Computing Research, 48*(2), 199-221. https://doi.org/10.2190/EC.48.2.e

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

Avcı, C., & Deniz, M. N. (2022). Computational thinking: Early childhood teachers' and prospective teachers' preconceptions and self-efficacy. *Education and Information Technologies, 27*(8), 11689-11713. https://doi.org/10.1007/s10639-022-11078-5

Bai, S., & Tian, P. (2025). Educational robotics may enhance students' conceptual knowledge, applied skills, and learning attitude in STEM education: A meta-analysis. *Educational Technology and Society, 28*(4), 274-303. https://doi.org/10.30191/ETS.202510_28(4).SP06

Bakala, E., Gerosa, A., Hourcade, J. P., & Tejera, G. (2021). Preschool children, robots, and computational thinking: A systematic review. *International Journal of Child-Computer Interaction, 29*, Article 100337. https://doi.org/10.1016/j.ijcci.2021.100337

Barker, C., Pistrang, N., & Elliott, R. (2015). *Research methods in clinical psychology: An introduction for students and practitioners* (3rd ed.). John Wiley & Sons. https://doi.org/10.1002/9781119154082

Bellas, F., Naya-Varela, M., Mallo, A., & Paz-Lopez, A. (2024). Education in the AI era: A long-term classroom technology based on intelligent robotics. *Humanities and Social Sciences Communications, 11*, Article 1425. https://doi.org/10.1057/s41599-024-03953-y

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

Blair, J., Czaja, R. F., & Blair, E. A. (2013). *Designing surveys: A guide to decisions and procedures*. SAGE. https://doi.org/10.4135/9781071909904

Bou Saad, R., Garcia, A. L., & Garcia, J. M. C. (2025). Mapping constructivist active learning for STEM: Toward sustainable education. *Sustainability, 17*(13), Article 6225. https://doi.org/10.3390/su17136225

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology, 3*(2), 77-101. https://doi.org/10.1191/1478088706qp063oa

Budiyanto, C. W., Fenyvesi, K., Lathifah, A., & Yuana, R. A. (2022). Computational thinking development: Benefiting from educational robotics in STEM teaching. *European Journal of Educational Research, 11*(4), 1997-2012. https://doi.org/10.12973/eu-jer.11.4.1997

Celik, I. (2023). Towards intelligent-TPACK: An empirical study on teachers' professional knowledge to ethically integrate artificial intelligence (AI)-based tools into education. *Computers in Human Behavior, 138*, Article 107468. https://doi.org/10.1016/j.chb.2022.107468

Chandra, Y., & Shang, L. (2019). Inductive coding. In *Qualitative research using R: A systematic approach* (pp. 91-106). Springer. https://doi.org/10.1007/978-981-13-3170-1_8

Cheng, L., Wang, X., & Ritzhaupt, A. D. (2023). The effects of computational thinking integration in STEM on students' learning performance in K-12 education: A meta-analysis. *Journal of Educational Computing Research, 61*(2), 416-443. https://doi.org/10.1177/07356331221114183

Ching, Y.-H., & Hsu, Y.-C. (2024). Educational robotics for developing computational thinking in young learners: A systematic review. *TechTrends, 68*(3), 423-434. https://doi.org/10.1007/s11528-023-00841-1

Christensen, R., Knezek, G., & Tyler-Wood, T. (2015). Alignment of hands-on STEM engagement activities with positive STEM dispositions in secondary school students. *Journal of Science Education and Technology, 24*(6), 898-909. https://doi.org/10.1007/s10956-015-9572-6

Chu, Y.-K., Liang, J.-C., & Tsai, M.-J. (2020). Elementary and middle school teachers' teaching attitude, belief, motivation and technological pedagogical content knowledge of robotics-based instruction. *International Journal on Digital Learning Technology, 12*(2), 75-97.

Cohen, J. (1988). *Statistical power analysis for the behavioural sciences*. Lawrence Erlbaum Associates.

Creswell, J. W., Plano Clark, V. L., Gutmann, M. L., & Hanson, W. E. (2003). Advanced mixed methods research designs. In *Handbook of mixed methods in social and behavioral research* (pp. 209-240). SAGE.

Crompton, H., & Sykora, C. (2021). Developing instructional technology standards for educators: A design-based research study. *Computers and Education Open, 2*, Article 100044. https://doi.org/10.1016/j.caeo.2021.100044

Dolgopolovas, V., & Dagiene, V. (2024). Competency-based TPACK approaches to computational thinking and integrated STEM: A conceptual exploration. *Computer Applications in Engineering Education, 32*(6), Article e22788. https://doi.org/10.1002/cae.22788

Dong, S., Zhi, R., & Gan, F. (2025). Integrating robotics in art education: Leveraging constructivist and experiential learning frameworks to enhance cognitive development, problem-solving skills and collaboration among diverse learners. *European Journal of Education, 60*(2), Article e70114. https://doi.org/10.1111/ejed.70114

Dong, W., Li, Y., Sun, L., & Liu, Y. (2024). Developing pre-service teachers' computational thinking: A systematic literature review. *International Journal of Technology and Design Education, 34*(1), 191-227. https://doi.org/10.1007/s10798-023-09811-3

Eguchi, A. (2014). Educational robotics for promoting 21st century skills. *Journal of Automation, Mobile Robotics and Intelligent Systems, 8*(1), 5-11. https://doi.org/10.14313/jamris_1-2014/1

Eguchi, A. (2022). AI-powered educational robotics as a learning tool to promote artificial intelligence and computer science education. In M. Merdan, W. Lepuschitz, G. Koppensteiner, R. Balogh, & D. Obdržálek (Eds.), *Robotics in education. RiE 2021. Advances in intelligent systems and computing, vol 1359* (pp. 279-287). Springer. https://doi.org/10.1007/978-3-030-82544-7_26

Eguchi, A. (2023). Machine learning application with AI-robotics tool – What we learned from pilot studies In J. M. Cascalho, M. O. Tokhi, M. F. Silva, A. Mendes, K. Goher, & M. Funk (Eds.), *Robotics in natural settings. CLAWAR 2022. Lecture notes in networks and systems, vol 530* (pp. 383-394). Springer. https://doi.org/10.1007/978-3-031-15226-9_36

Falloon, G. (2024). Advancing young students computational thinking: An investigation of structured curriculum in early years primary schooling. *Computers and Education, 216*, Article 105045. https://doi.org/10.1016/j.compedu.2024.105045

Fereday, J., Adelaide, N., Australia, S., & Eimear Muir-Cochrane, A. (2006). Demonstrating rigor using thematic analysis: A hybrid approach of inductive and deductive coding and theme development. *International Journal of Qualitative Methods, 1*(5), 80-92. https://doi.org/10.1177/160940690600500107

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(1), 39-50. https://doi.org/10.1177/002224378101800104

Fung, K. Y., Fung, K. C., Lui, T. L. R., Sin, K. F., Lee, L. H., Qu, H., & Song, S. (2025). Exploring the impact of robot interaction on learning engagement: A comparative study of two multi-modal robots. *Smart Learning Environments, 12*, Article 12. https://doi.org/10.1186/s40561-024-00362-1

Gonscherowski, P., & Rott, B. (2025). A systematic review of the literature on TPACK instruments used with pre-service teachers from 2017 to 2023 focused on selecting digital resources. *Journal of Computers in Education, 13*(3), 945-982. https://doi.org/10.1007/s40692-025-00379-6

Grover, S., & Pea, R. (2013). Computational thinking in K-12: A review of the state of the field. *Educational Researcher, 42*(1), 38-43. https://doi.org/10.3102/0013189X12463051

Haddadin, S. (2024). The Franka Emika robot: A standard platform in robotics research. *IEEE Robotics & Automation Magazine, 31*(4), 136-148. https://doi.org/10.1109/MRA.2024.3451788

Haidegger, T., Mai, V., Mörch, C. M., Boesl, D. O., Jacobs, A., Rao R, B., Khamis, A., Lach, L., & Vanderborght, B. (2023). Robotics: Enabler and inhibitor of the sustainable development goals. *Sustainable Production and Consumption, 43*, 422-434. https://doi.org/10.1016/j.spc.2023.11.011

Hair, J. F., Babin, B. J., & Krey, N. (2017). Covariance-based structural equation modeling in the *Journal of Advertising*: Review and recommendations. *Journal of Advertising, 46*(1), 163-177. https://doi.org/10.1080/00913367.2017.1281777

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review, 31*(1), 2-24. https://doi.org/10.1108/EBR-11-2018-0203

Henze, J., Schatz, C., Malik, S., & Bresges, A. (2022). How might we raise interest in robotics, coding, artificial intelligence, STEAM and sustainable development in university and on-the-job teacher training? *Frontiers in Education, 7*. https://doi.org/10.3389/feduc.2022.872637

Hosseini, Z. (2015). Development of technological pedagogical content knowledge through constructionist activities. *Procedia-Social and Behavioral Sciences, 182*, 98-103. https://doi.org/10.1016/j.sbspro.2015.04.743

Hsu, C.-Y., & Tsai, M.-J. (2024). Predicting robotics pedagogical content knowledge: The role of computational and design thinking dispositions via teaching beliefs. *Journal of Educational Computing Research, 62*(5), 1159-1181. https://doi.org/10.1177/07356331241236882

Hsu, T.-C., & Chen, M.-S. (2025). Effects of students using different learning approaches for learning computational thinking and AI applications. *Education and Information Technologies, 30*(6), 7549-7571. https://doi.org/10.1007/s10639-024-13116-w

Hulland, J. (1999). Use of partial least squares (PLS) in strategic management research: A review of four recent studies. *Strategic Management Journal, 20*(2), 195-204. https://doi.org/10.1002/(SICI)1097-0266(199902)20:2<195::AID-SMJ13>3.0.CO;2-7

Isnaini, R., Budiyanto, C., & Widiastuti, I. (2019). Robotics-based learning to support computational thinking skills in early childhood. *AIP Conference Proceedings, 2194*(1), Article 020044. https://doi.org/10.1063/1.5139776

Jamal, N. N., Jawawi, D. N. A., Hassan, R., Mohamad, R., Halim, S. A., Saadon, N. A., Isa, M. A., & Hamed, H. N. A. (2024). Adaptive learning framework for learning computational thinking using educational robotics. *Computer Applications in Engineering Education, 32*(4), Article e22732. https://doi.org/10.1002/cae.22732

Kerimbayev, N., Nurym, N., Akramova, A., & Abdykarimova, S. (2023). Educational robotics: Development of computational thinking in collaborative online learning. *Education and Information Technologies, 28*(11), 14987-15009. https://doi.org/10.1007/s10639-023-11806-5

Kert, S. B., Erkoç, M. F., & Yeni, S. (2020). The effect of robotics on six graders' academic achievement, computational thinking skills and conceptual knowledge levels. *Thinking Skills and Creativity, 38*, Article 100714. https://doi.org/10.1016/j.tsc.2020.100714

Kim, C., Belland, B. R., Vasconcelos, L., & Hill, R. B. (2024). Playful programming, social resilience, and persistent actions as drivers of preservice early childhood teachers' engagement in computer science. *Sage Open, 14*(4). https://doi.org/10.1177/21582440241284488

Kong, S. C., Lai, M., & Sun, D. (2020). Teacher development in computational thinking: Design and learning outcomes of programming concepts, practices and pedagogy. *Computers and Education, 151*, Article 103872. https://doi.org/10.1016/j.compedu.2020.103872

Kong, S.-C., & Lai, M. (2022). A proposed computational thinking teacher development framework for K-12 guided by the TPACK model. *Journal of Computers in Education, 9*(3), 379-402. https://doi.org/10.1007/s40692-021-00207-7

Kong, S.-C., Lai, M., & Li, Y. (2023). Scaling up a teacher development programme for sustainable computational thinking education: TPACK surveys, concept tests and primary school visits. *Computers & Education, 194*, Article 104707. https://doi.org/10.1016/j.compedu.2022.104707

Lampropoulos, G. (2025). Social robots in education: Current trends and future perspectives. *Information, 16*(1), Article 29. https://doi.org/10.3390/info16010029

Landis, J. R., & Koch, G. G. (1977). The measurement of observer agreement for categorical data. *Biometrics, 33*(1), 159-174. https://doi.org/10.2307/2529310

Lane, W. B., Galanti, T. M., & Rozas, X. L. (2023). Teacher re-novicing on the path to integrating computational thinking in high school physics instruction. *Journal for STEM Education Research, 6*(2), 302-325. https://doi.org/10.1007/s41979-023-00100-1

Lee, B., Ku, S., & Ko, K. (2025). AI robots promote South Korean preschoolers' AI literacy and computational thinking. *Family Relations, 74*(3), 1354-1375. https://doi.org/10.1111/fare.13189

Li, Q. (2021). Computational thinking and teacher education: An expert interview study. *Human Behavior and Emerging Technologies, 3*(2), 324-338. https://doi.org/10.1002/hbe2.224

Li, Y., Schoenfeld, A. H., diSessa, A. A., Graesser, A. C., Benson, L. C., English, L. D., & Duschl, R. A. (2020). On computational thinking and STEM education. *Journal for STEM Education Research, 3*(2), 147-166. https://doi.org/10.1007/s41979-020-00044-w

Lu, S., Nuryana, Z., Ni, X., Xu, W., & Alias, M. N. (2025). A decade of educational robotics: Trends and SDG contributions. *Humanities and Social Sciences Communications, 12*, Article 1356. https://doi.org/10.1057/s41599-025-05663-5

M. Thamrin, N., Irawan, A., Zulkifli, Z., Al Junid, S. A. M., Megat Ali, M. S. A., & P. P. Abdul Majeed, A. (2026). Robotics and artificial intelligence: Autonomous learning in education. In *Robotics in education. SpringerBriefs in applied sciences and technology* (pp. 55-72). Springer. https://doi.org/10.1007/978-981-95-3548-4_5

Macann, V., Yadav, A., Ukkonen, A., Lee, H., & D'Amico, A. (2026). Computational thinking integrated science: How professional development can support elementary teachers. *Journal of Computers in Education, 13*(2), 735-767. https://doi.org/10.1007/s40692-025-00370-1

MacCallum, K. (2025). Integrating computational thinking through digital creation: The (TPAC)²K model. *Teaching and Teacher Education, 161*, Article 105056. https://doi.org/10.1016/j.tate.2025.105056

Martínez Rojas, E., Valencia-Arias, A., Vásquez Coronado, M. H., Barandiarán Gamarra, J. M., Agudelo-Ceballos, E., Benjumea-Arias, M. L., & Vega Mori, L. (2025). Educational robotics for primary education: An analysis of research trends. *Eurasia Journal of Mathematics, Science and Technology Education, 21*(3), Article em2602. https://doi.org/10.29333/ejmste/16050

Mishra, P., & Koehler, M. J. (2006). Technological pedagogical content knowledge: A framework for teacher knowledge. *Teachers College Record: The Voice of Scholarship in Education, 108*(6), 1017-1054. https://doi.org/10.1111/j.1467-9620.2006.00684.x

Moore, A. M., Fairhurst, P., Correia, C. F., Harrison, C., & Bennett, J. M. (2020). Science practical work in a COVID-19 world: Are teacher demonstrations, videos and textbooks effective replacements for hands-on practical activities? *School Science Review, 102*(378), 7-12.

Moreno Palma, N., Berral Ortiz, B., Fernández Fernández, C. R., & Victoria Maldonado, J. J. (2025). Pensamiento computacional en la educación básica a través de la robótica educativa: Una revisión sistemática [Computational thinking in basic education through educational robotics: A systematic review]. *European Public & Social Innovation Review, 10*, 1-20. https://doi.org/10.31637/epsir-2025-1099

Nannim, F. A., Ibezim, N. E., Oguguo, B. C. E., & Nwangwu, E. C. (2024). Effect of project-based Arduino robot application on trainee teachers computational thinking in robotics programming course. *Education and Information Technologies, 29*(10), 13155-13170. https://doi.org/10.1007/s10639-023-12380-6

Noh, J., & Lee, J. (2020). Effects of robotics programming on the computational thinking and creativity of elementary school students. *Educational Technology Research and Development, 68*(1), 463-484. https://doi.org/10.1007/s11423-019-09708-w

Nunnally, J. C., & Bernstein, I. H. (1994). *Psychometric theory* (3rd ed.). McGraw-Hill.

Okundaye, O., Natarajarathinam, M., Qiu, S., Kuttolamadom, M. A., Chu, S., & Quek, F. (2022). Making STEM real: The design of a making-production model for hands-on STEM learning. *European Journal of Engineering Education, 47*(6), 1122-1143. https://doi.org/10.1080/03043797.2022.2121685

Pajchel, K., Mifsud, L., Frågåt, T., Rehder, M. M., Juuti, K., Bogar, Y., Lavonen, J., Schrøder, V., Aalbergsjø, S. G., & Rognes, A. (2024). Sign of the times: The framing of computational thinking in Danish, Finnish, and Norwegian curricula. *Nordic Journal of Comparative and International Education, 8*(4). https://doi.org/10.7577/njcie.5744

Papert, S. (1993). *The children's machine: Rethinking school in the age of the computer*. Basic Books.

Papert, S. (2020). *Mindstorms: Children, computers, and powerful ideas*. Basic Books.

Papert, S., & Harel, I. (2002). Situating constructionism. In *Proceedings of the INCAE*.

Proctor, C. (2023). Computational thinking. In *International encyclopedia of education* (pp. 88-95). Elsevier. https://doi.org/10.1016/B978-0-12-818630-5.13078-7

Puzio, A. (2025). Robot, let us pray! Can and should robots have religious functions? An ethical exploration of religious robots. *AI & SOCIETY, 40*(2), 1019-1035. https://doi.org/10.1007/s00146-023-01812-z

Qu, J. R., & Fok, P. K. (2022). Cultivating students' computational thinking through student-robot interactions in robotics education. *International Journal of Technology and Design Education, 32*(4), 1983-2002. https://doi.org/10.1007/s10798-021-09677-3

Saritepeci, M. (2022). Modelling the effect of TPACK and computational thinking on classroom management in technology enriched courses. *Technology, Knowledge and Learning, 27*(4), 1155-1169. https://doi.org/10.1007/s10758-021-09529-y

Scaradozzi, D., Screpanti, L., & Cesaretti, L. (2019). Towards a definition of educational robotics: A classification of tools, experiences and assessments. In L. Daniela (Ed.), *Smart learning with educational robotics* (pp. 63-92). Springer. https://doi.org/10.1007/978-3-030-19913-5_3

Schmidt, D. A., Baran, E., Thompson, A. D., Mishra, P., Koehler, M. J., & Shin, T. S. (2009). Technological pedagogical content knowledge (TPACK): The development and validation of an assessment instrument for preservice teachers. *Journal of Research on Technology in Education, 42*(2), 123-149. https://doi.org/10.1080/15391523.2009.10782544

Setiyawan, A., Soeharto, S., Wijaya, T. T., Korenova, L., & Lavicza, Z. (2025). Measuring teachers' competencies for AI integration: Development and validation of the AI-TPACK in vocational education. *Computers and Education Open, 9*, Article 100319. https://doi.org/10.1016/j.caeo.2025.100319

Shulman, L. S. (1987). Knowledge and teaching: Foundations of the new reform. *Harvard Education Review, 57*(1), 1-21. https://doi.org/10.17763/haer.57.1.j463w79r56455411

Slavin, R. E. (2018). *Educational psychology: Theory and practice* (12th ed.). Pearson.

Su, W.-S., Hwang, G.-J., Yin, C., & Chang, C.-Y. (2025). Exploring gender and educational background effects on 21st-century competencies in robot-integrated STEM education: The role of learning attitudes and satisfaction. *Educational Technology and Society, 28*(4), 394-410. https://doi.org/10.30191/ETS.202510_28(4).SP11

Umutlu, D. (2022). TPACK leveraged: A redesigned online educational technology course for STEM preservice teachers. *Australasian Journal of Educational Technology, 38*(3), 99-116. https://doi.org/10.14742/ajet.4773

Vasconcelos, L., Arslan-Ari, I., Miller, B., & Gonzalez-Tapia, R. (2025). Robotics in early childhood STEM education (REC-STEMEd): The impact on preservice teachers' attitudes and intentions toward computational thinking. *Education and Information Technologies, 30*(13), 18347-18374. https://doi.org/10.1007/s10639-025-13529-1

Wang, C., Shen, J., & Chao, J. (2022). Integrating computational thinking in STEM education: A literature review. *International Journal of Science and Mathematics Education, 20*(8), 1949-1972. https://doi.org/10.1007/s10763-021-10227-5

Wang, H., Luo, N., Zhou, T., & Yang, S. (2024). Physical robots in education: A systematic review based on the technological pedagogical content knowledge framework. *Sustainability, 16*(12), Article 4987. https://doi.org/10.3390/su16124987

Wang, W., & Shen, G. (2026). Educational robotics and student development: A second-order meta-analysis. *Journal of Research on Technology in Education*. https://doi.org/10.1080/15391523.2025.2598241

Williams, M., & Moser, T. (2019). The art of coding and thematic exploration in qualitative research. *International Management Review, 15*, Article 45.

Wing, J. M. (2006). Computational thinking. *Communications of the ACM, 49*(3), 33-35. https://doi.org/10.1145/1118178.1118215

Wing, J. M. (2017). Computational thinking's influence on research and education for all. *Italian Journal of Educational Technology, 25*(2), 7-14. https://doi.org/10.17471/2499-4324/922

Woolfolk, A. (2016). *Educational psychology* (13th ed.). Pearson.

Yadav, A., Mayfield, C., Zhou, N., Hambrusch, S., & Korb, J. T. (2014). Computational thinking in elementary and secondary teacher education. *ACM Transactions on Computing Education, 14*(1), Article 5. https://doi.org/10.1145/2576872

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

Yang, S., Baird, M., O'Rourke, E., Brennan, K., & Schneider, B. (2024). Decoding debugging instruction: A systematic literature review of debugging interventions. *ACM Transactions on Computing Education, 24*(4), 1-44. https://doi.org/10.1145/3690652

Yang, W. (2025). A three-phase professional development approach to improving robotics pedagogical knowledge and computational thinking attitude of early childhood teachers. *Computers & Education, 231*, Article 105282. https://doi.org/10.1016/j.compedu.2025.105282

Yang, Y., Long, Y., Sun, D., Van Aalst, J., & Cheng, S. (2020). Fostering students' creativity via educational robotics: An investigation of teachers' pedagogical practices based on teacher interviews. *British Journal of Educational Technology, 51*(5), 1826-1842. https://doi.org/10.1111/bjet.12985

Yanış, H., & Yürük, N. (2021). Development, validity, and reliability of an educational robotics based technological pedagogical content knowledge self-efficacy scale. *Journal of Research on Technology in Education, 53*(4), 375-403. https://doi.org/10.1080/15391523.2020.1784065

Zollman, A. (2012). Learning for STEM literacy: STEM literacy for learning. *School Science and Mathematics, 112*(1), 12-19. https://doi.org/10.1111/j.1949-8594.2012.00101.x

Zviel-Girshin, R., & Rosenberg, N. (2025). Enhancing early STEM engagement: The impact of inquiry-based robotics projects on first-grade students' problem-solving self-efficacy and collaborative attitudes. *Education Sciences, 15*(10), Article 1404. https://doi.org/10.3390/educsci15101404

APPENDIX A

Table A1. Instrument of CT and robotic TPACK

Dimension	Item
CT	
Abstraction1	I can identify the essential information needed to solve a problem when working with robotics.
Abstraction2	I can understand how the use of light and sound sensors in robotics can be simplified to be taught to elementary school students.
Abstraction3	I feel able to filter relevant information about light and sound sensors to make it easier for students to understand.
Generalization1	I can connect the basic principles learned in this workshop (light and sound sensors in robots) with my previous learning experiences.
Generalization2	I can apply solutions from previous robotics problems to solve new problems with similar patterns
Generalization3	I can use the principles learned in this workshop to help students understand technology and science concepts more easily.
Decomposition1	I can break down a complex robotics problem into smaller, manageable parts.
Decomposition2	I find it easy to break down technical problems in robot programming, such as connecting light and sound sensors with appropriate algorithms to make the robot move.
Decomposition3	I can easily divide the process of building a robot using light and sound sensors into smaller parts to be completed step by step.
Algorithmic thinking1	I find it easy to design step-by-step procedures (algorithms) to control robots using light and sound sensors in this workshop.
Algorithmic thinking2	I can write the sequence of steps required to make a robot move based on light and sound sensors and implement those steps in program code.
Algorithmic thinking3	I can develop a logical sequence of steps to solve problems when working with robotics
Debugging1	I can identify and correct errors when a robotics system or program does not work as expected
Debugging2	I find it easy to identify errors in the program and fix them so that the robot moves according to the instructions from the light and sound sensors.
Debugging3	I feel comfortable revising and retesting the program when the robot does not function as expected after programming.
TPACK	
TPACK1	I am able to modify technology to design teaching modules (lesson plans, learning materials, assessments, and media) for elementary school science topics.
TPACK2	I can design learning activities that appropriately integrate technology with subject content.
TPACK3	I am able to use technology to design teaching modules (lesson plans, learning materials, assessments, and media) for elementary school science topics.
TPACK4	I can use technology to support effective teaching and student learning.
TPACK5	I can use technology to implement learning integrated with instructional strategies or methods (such as cooperative learning, direct instruction, inquiry learning, problem-based learning, project-based learning, etc.) in elementary school science classes.
TPACK6	I can adapt technology to implement learning integrated with instructional strategies or methods (such as cooperative learning, direct instruction, inquiry learning, problem-based learning, project-based learning, etc.) in elementary school science classes.
TPACK7	I can evaluate the effectiveness of technology integration in achieving learning objectives.
TPACK8	I can modify technology to evaluate learning (such as Quizizz, Google Forms, Wordwall, etc.) in elementary school science topics.
TPACK9	I can adapt technology to evaluate students' understanding and performance in elementary school science.
RPCK	
RPCK3	I am able to integrate robotics as a medium for designing learning modules (lesson plans, textbooks, etc.) that align with the concepts, laws, and structure of elementary school science content and its applications.
RPCK4	I can develop robotics to implement learning integrated with instructional strategies or methods (such as cooperative learning, direct instruction, inquiry learning, problem-based learning, project-based learning, etc.) in elementary school science classes.
RPCK5	I am able to connect Arduino-based robotics media with science learning.
RPCK6	I can develop evaluation tools to assess elementary school science products based on Arduino robotics.