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Data Literacy and Computational Thinking Among Secondary Science Teachers: A Quantitative Study of Levels, Differences and Instructional Integration

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Abstract
Objectives. This study examined the levels of data literacy (DL) and computational thinking (CT) skills among secondary science teachers, the extent of their integration into science instruction, and the relationships between these competencies and instructional integration.
Materials and Methods. Using a descriptive-correlational design, 53 secondary science teachers in Masbate, Philippines, completed three researcher-developed Likert-type instruments measuring DL, CT, and DL-CT integration into science instruction. Data were analyzed using means and standard deviations, the Wilcoxon Signed-Rank Test, and Spearman rank-order correlation.
Results. Teachers rated themselves Proficient in both DL ($M = 3.92$, $SD = 0.63$) and CT ($M = 3.84$, $SD = 0.64$), with a statistically significant difference between the two, $W = 288.00$, $p = .040$, $r = .28$. Teachers reported a Highly Integrated level of DL-CT instructional integration ($M = 3.90$, $SD = 0.82$). Spearman correlations revealed strong positive associations of both DL ($rs = .740$) and CT ($rs = .757$) with integration, both $p < .001$, with algorithmic thinking emerging as the single strongest correlate ($rs = .785$).
Conclusion. Secondary science teachers demonstrated proficient but uneven data literacy and computational thinking skills, with abstraction and access to computational tools emerging as relative weaknesses. Both competencies played a substantial and complementary role in supporting integrated science instruction, and targeted professional development addressing these weaker areas is recommended.
Keywords: data literacy, computational thinking, science education, instructional integration, secondary teachers.

Introduction

The 21st century has transformed the learning competencies that students must possess to thrive in an era defined by data and technology. Among the most consequential of these competencies are data literacy and computational thinking, two interconnected skill sets that have gained substantial recognition in educational policy, curriculum reform and pedagogical scholarship worldwide. In the domain of science education, these competencies are not merely supplementary skills but fundamental epistemic tools that align directly with the nature of scientific inquiry, which is inherently quantitative, data intensive and systematic (National Research Council, 2012; Weintrop et al., 2016).

Ridsdale et al. (2015) defined data literacy as the ability to collect, manage, evaluate and apply data in a critical and meaningful manner. It is increasingly recognized as a foundational competency for informed citizenship and scientific participation. In the science classroom, students who are data literate can engage meaningfully with empirical evidence, interpret graphs and tables, evaluate the validity and reliability of scientific claims and draw evidence-based conclusions (Kjelvik & Schultheis, 2019). These capabilities mirror the authentic practices of scientists and are central to the scientific inquiry standards embedded in contemporary science curriculum frameworks (NGSS Lead States, 2013).

Meanwhile, computational thinking (CT), as articulated by Wing (2006) in her landmark formulation, refers to the cognitive processes involved in formulating problems and their solutions in ways that can be carried out by an information-processing agent. CT encompasses decomposition (breaking complex real-world problems into manageable parts), pattern recognition (identifying regularities and trends), abstraction (filtering relevant from irrelevant information) and algorithmic thinking (designing step-by-step solutions).

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Broadly speaking, computational thinking entails mathematical reasoning, design-based thinking and the ability to reason at several levels of abstraction (Kramer, 2007; Wing, 2008). Additionally, it involves applying these types of reasoning to contextual problem solving (Guzdial, 2008; Wing, 2008). In science education, CT provides students with powerful strategies for modeling natural phenomena, analyzing large datasets, simulating complex systems and designing controlled experiments (Grover & Pea, 2013; Weintrop et al., 2016).

The integration of data literacy and computational thinking into science instruction has received significant impetus from several influential policy documents and curriculum frameworks. The Next Generation Science Standards (NGSS) in the United States explicitly position data analysis, mathematical and computational thinking and the use of models as core scientific and engineering practices (NGSS Lead States, 2013). Similarly, the National Research Council's Framework for K-12 Science Education identifies computational tools as essential instruments for contemporary scientific practice. These frameworks reflect a broader recognition that science education in the 21st century must prepare students not only to understand scientific content but to engage in the processes and practices that constitute authentic scientific work.

Despite this growing attention, empirical evidence suggests a significant gap between the theoretical articulation of these competencies in curriculum documents and their actual realization in classroom practice. Barr and Stephenson (2011) documented widespread unpreparedness among teachers to integrate computational thinking into their instructional practice, indicating that most K-12 teachers had received little or no professional preparation in this area. Lee (2025) stressed that teachers often recognize and appreciate the value of data but remain uncertain due to low self-efficacy in independently analyzing data or using complex computational tools. Similarly, Carlson et al. (2011) found that even in higher education, students' data information literacy skills were frequently insufficient for the demands of research and evidence-based learning.

In the Philippines, the K to 12 Basic Education Curriculum reform, implemented by the Department of Education (DepEd) beginning in 2012, explicitly articulates the goal of developing scientifically, technologically and mathematically literate Filipinos who are capable of critical thinking and problem solving (Department of Education, 2016). The Senior High School Science curriculum includes components that implicitly demand data literacy and computational thinking, such as research-based learning, data-driven argumentation and laboratory investigations requiring quantitative analysis. However, the extent to which Filipino science teachers are equipped to facilitate the development of these competencies in their students, and the degree to which these competencies are systematically addressed in science instruction, remain empirically underexplored.

This study therefore seeks to provide empirical evidence on the self-assessed level of data literacy and computational thinking skills among science teachers, the extent of their integration into science instruction and the relationship between these two core competencies in the context of Philippine secondary science education. By employing a quantitative, descriptive-correlational research design, this study aims to generate data that are both statistically rigorous and practically actionable for curriculum developers, school administrators and science educators and replicable of future researchers.

Specifically, the study sought to determine the level of data literacy of secondary science teachers along the dimensions of data collection and management, data analysis and interpretation, data visualization and data-based decision making; the level of their computational thinking skills along the dimensions of decomposition, pattern recognition, abstraction and algorithmic thinking; whether a statistically significant difference exists between their self-assessed data literacy and computational thinking skills; the extent to which data literacy and computational thinking skills are integrated into science instruction; and the correlation between this instructional integration and each of the two competencies.

Review of Related Literature

Data Literacy in Science Education

The concept of data literacy has evolved substantially over the past two decades. Ridsdale et al. (2015) proposed a comprehensive data literacy framework identifying core competencies, namely data collection, data management, data evaluation, data analysis, data visualization and data-based decision making. This multidimensional view positioned data literacy not as a single homogeneous skill but as a complex competency that develops progressively and must be supported by intentional instructional and institutional conditions. Calzada Prado and Marzal (2013) offered a complementary perspective from the information literacy tradition, emphasizing the critical and evaluative dimensions of data literacy, particularly the capacity to assess the quality, reliability and limitations of data.

In the context of teacher professional development, Pastore et al. (2025) conducted a scoping review of teacher data literacy research published between 2020 and 2024 and found that most studies reported moderate to high data literacy levels among in-service teachers who had received structured professional development. Mandinach and Schildkamp (2021) further argued that when teachers view data as actionable evidence for improving instruction, decision-making naturally becomes the most strongly developed data literacy dimension. However, Sandoval-Ríos et al. (2025) noted a persistent skills gap in data literacy training within teacher education programs, particularly in developing-country contexts where statistical and data skills are often excluded from pre-service curricula.

Within data literacy, visualization has been identified as a particularly challenging dimension. Laramee (2023) emphasized that visualization remains cognitively complex, requiring learners to simultaneously navigate statistical, contextual and communicative layers of meaning. Fernandez Nieto et al. (2022) similarly noted that data visualization tasks can exceed the professional skill set of educators without strong analytical foundations. Wilkerson et al. (2025) found that teachers with higher visualization literacy were more effective in facilitating student-centered data visualization discussions in science classrooms.

Computational Thinking in Science Education

Wing's (2006) seminal framework conceptualized computational thinking as a universally applicable cognitive process extending across all disciplines. She argued that CT involves formulating problems and their solutions in ways that make them tractable for computational processing, emphasizing that decomposition, pattern recognition, abstraction and algorithm design are fundamental intellectual tools. Grover and Pea (2013) subsequently elaborated this framework for K-12 contexts, while Weintrop et al. (2016) further operationalized CT practices for STEM education, namely data practices, modeling and simulation practices, computational problem-solving practices and systems-thinking practices.

Research has consistently identified abstraction as the most challenging CT dimension. Oser et al. (2025), in a systematic review, concluded that abstraction remains the least proficiently developed CT skill in K-12 education, noting significant inconsistencies in how it is conceptualized and taught. Asif et al. (2024) observed that while teachers can engage in surface-level abstraction, deeper forms remain challenging without dedicated professional learning. Asif et al. (2023) further found that teachers often simplify abstraction to merely ignoring details, missing its full computational meaning as level-switching and information suppression.

Mertens and Colunga (2025) identified decomposition as the most cognitively accessible CT component, as it maps naturally onto scientific problem-solving processes such as experimental design. In contrast, Kong et al. (2020) and Rich et al. (2021) reported that even after targeted professional development, many K-12 teachers continued to demonstrate inconsistent CT proficiency. Hsu et al. (2024), in their systematic review, documented that despite growing momentum in CT professional development, there remains a notable absence of consensus on how to assess and build teachers' CT knowledge.

Integration of Data Literacy and Computational Thinking into Instruction

Coenraad et al. (2022) analyzed CT integration in elementary science lesson plans and found that the most successful integration sites were those connected to authentic data analysis tasks embedded in real-world science contexts. Moon et al. (2023) observed that teachers who integrated CT through contextual, problem-based science tasks demonstrated stronger instructional coherence than those who taught CT as a standalone activity. However, the UNESCO Global Education Monitoring Report (2023) documented that digital tool use in science classrooms remains limited even in high-income countries, with simulation and modeling software available to fewer than one-third of students in many contexts.

Angeli et al. (2016) cautioned that the pedagogical integration of computational tools requires dedicated institutional support, including infrastructure provisioning, technical assistance and subject-specific training. Kadioglu-Akbulut et al. (2023) highlighted similar concerns in their study of science teachers' TPACK (Technological Pedagogical Content Knowledge) levels. Lim et al. (2023) found that even when teachers held strong CT beliefs and pedagogical knowledge, technology-tool integration lagged behind due to insufficient discipline-specific training. Cui and Zhang (2022) argued that teacher data competencies must be integrated with pedagogical content knowledge rather than treated as standalone technical skills, a position supported by the broader TPACK-integrated data literacy framework.

Theoretical Framework

This study is grounded in the convergence of three theoretical foundations, namely Constructivism, Wing's Computational Thinking Framework and the Data Literacy Framework.

Constructivism, as elaborated in the foundational works of Piaget (1952) and Vygotsky (1978), posits that learners actively construct knowledge through their interactions with the environment and with other learners, rather than passively receiving information transmitted by teachers. Piaget's theory emphasizes the role of active engagement, assimilation and accommodation in building increasingly sophisticated cognitive schemas. Vygotsky's sociocultural constructivism extends this view by highlighting the central role of social interaction, language and cultural tools, including computational and data tools, in mediating higher-order cognitive development. In the context of science education, constructivism provides the theoretical basis for viewing data literacy and computational thinking not as isolated technical skills to be taught demonstratively, but as higher-order cognitive capacities developed through active, inquiry-based engagement with authentic data and computational problems. Vygotsky's Zone of Proximal Development is particularly relevant, as it underscores the importance of teachers' own competence in scaffolding students' development of these complex skills.

Wing's (2006) computational thinking framework and its subsequent elaborations by Grover and Pea (2013) and Weintrop et al. (2016) provide the conceptual structure for the CT construct in this study. These operationalizations directly inform the measurement of decomposition, pattern recognition, abstraction and algorithmic thinking as applied to science education contexts.

The data literacy framework articulated by Ridsdale et al. (2015), complemented by Calzada Prado and Marzal's (2013) emphasis on the evaluative dimensions of data literacy, provides the conceptual foundation for the DL construct measured in this study. Together, these three frameworks generate the expectation that teachers who possess stronger data literacy and computational thinking skills will be better equipped to design, implement and sustain instruction that integrates these competencies authentically into science learning.

Materials and Methods

Study Participants

This study utilized purposive sampling (Etikan et al., 2016) to select respondents based on criteria directly aligned with the research objectives. A total of 53 secondary science teachers from selected high schools in Masbate, Philippines participated in the study. All respondents were currently teaching science subjects in Grades 7 to 12 under the K to 12 curriculum and were assigned to teach Earth Science, Biology, Chemistry, Physics or Integrated Science. All were employed by the Department of Education (DepEd) in the province of Masbate during the data gathering period. Teachers were included regardless of their years in the teaching profession, which allowed the sample to represent a wide range of teaching experience rather than a single career stage. It should be acknowledged that the use of purposive sampling with a modest sample size (n = 53) limits the generalizability of the findings to the broader population of Filipino secondary science teachers, and the findings are therefore intended to be suggestive of patterns warranting further investigation with larger, probability-based samples from multiple provinces and regions.

Study Organization

This study employed a descriptive-correlational research design, appropriate when a study seeks to measure and describe existing phenomena and examine statistical relationships among variables without manipulation or intervention (Creswell, 2014). The study utilized three researcher-developed instruments, namely the Data Literacy Scale (DLS), the Computational Thinking Skills Scale (CTSS) and the Data Literacy and Computational Thinking Skills Integration in Science Instruction Scale (DLCTSIS), developed based on the Data Literacy Framework (Calzada Prado & Marzal, 2013; Ridsdale et al., 2015) and the Computational Thinking Framework (Weintrop et al., 2016; Wing, 2006). All three instruments were subjected to content validation by a panel of science education experts and pilot tested with 20 science teachers who were not included in the actual study sample. The DLS is a 16-item Likert-type scale measuring data collection and management, data analysis and interpretation, data visualization and data-based decision making, with items rated from 5 (Expert) to 1 (Novice) and a pilot Cronbach's alpha of 0.93. The CTSS is a 16-item Likert-type scale measuring decomposition, pattern recognition, abstraction and algorithmic thinking, rated on the same scale, with a pilot Cronbach's alpha of 0.93. The DLCTSIS is a 10-item Likert-type scale with indicators adapted from the DL framework, the CT framework, the Next Generation Science Standards (NGSS Lead States, 2013) and the statistical thinking framework of Wild and Pfannkuch (1999), rated from 5 (Fully Integrated) to 1 (Not Integrated At All), with a pilot Cronbach's alpha of 0.91 (all interpreted as Excellent per George & Mallery, 2019). Data collection proceeded as follows. An official letter of permission was first secured from the DepEd Masbate Division Office. Survey questionnaires, together with a Participant Information Sheet and a consent form, were then distributed to all qualified respondents through Google Forms, and completed questionnaires were gathered within one week of distribution. All respondents were informed of the purpose of the study, the nature of the data collected, the voluntary nature of participation, their right to withdraw at any time and the confidentiality and data protection measures in place, and the survey proceeded only upon affirmative consent. Participation was entirely voluntary, with no incentive, coercion or pressure applied, and all data were stored on an access-controlled server to be deleted following the prescribed retention period. This study was conducted in compliance with Republic Act No. 10173, the Data Privacy Act of 2012 of the Philippines. Finally, all valid responses were encoded into a statistical analysis software database for analysis.

Statistical Analysis

The data analysis procedure utilized both descriptive and inferential statistics. The Shapiro-Wilk test was used to assess the normality of data distributions, which informed the selection of parametric or non-parametric procedures. To address the levels of data literacy, computational thinking skills and their integration into science instruction, means, standard deviations and verbal interpretations were computed. To analyze whether a significant difference exists between data literacy and computational thinking skills, the Wilcoxon Signed-Rank Test was employed as the appropriate non-parametric alternative to the paired t-test, given that both variables violated the normality assumption. To determine the correlations between data literacy, computational thinking skills and their integration into science instruction, Spearman's rank-order correlation (rs) was used given the non-normal distributions. The following interpretation thresholds were applied. Values from 0.00 to 0.19 indicate negligible correlation, 0.20 to 0.39 weak correlation, 0.40 to 0.69 moderate correlation, 0.70 to 0.89 strong correlation and 0.90 to 1.00 very strong correlation.

Results

Level of Data Literacy of Secondary Science Teachers

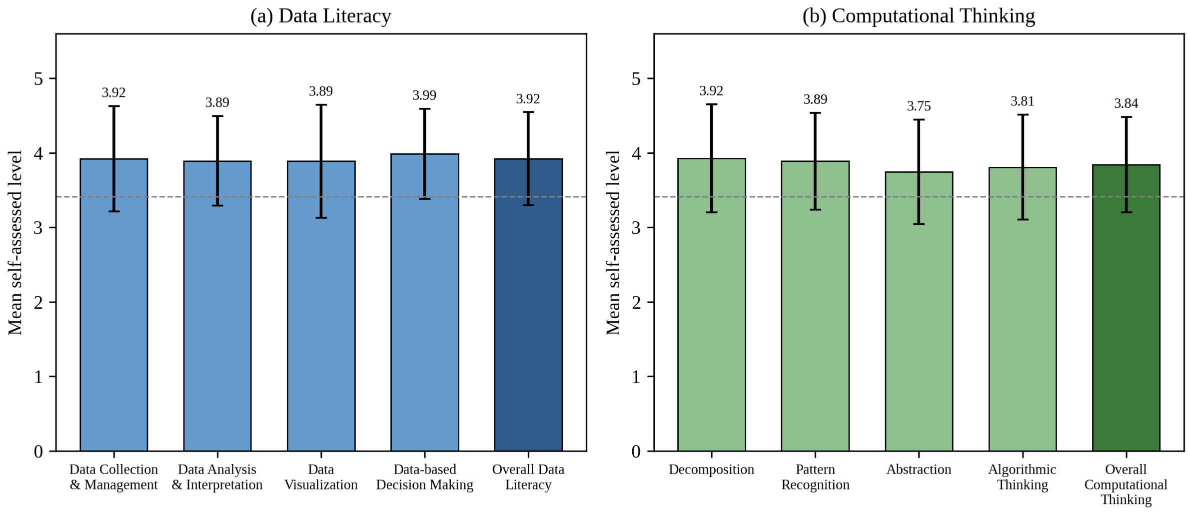
Table 1 and Figure 1(a) present the domain-level means and standard deviations for all 53 respondents across the four data literacy dimensions. All four dimensions were rated at the Proficient level (M range = 3.89 to 3.99). Data-based decision making received the highest mean (M = 3.99, SD = 0.60), followed by data collection and management (M = 3.92, SD = 0.71), data analysis and interpretation (M = 3.89, SD = 0.60) and data visualization (M = 3.89, SD = 0.76). The overall data literacy mean of 3.92 (SD = 0.63) falls within the Proficient range (3.41 to 4.20).

Table 1. Level of Data Literacy of Secondary Science Teachers

Domain	n	M	SD	Level
Data Collection and Management	53	3.92	0.71	Proficient
Data Analysis and Interpretation	53	3.89	0.60	Proficient
Data Visualization	53	3.89	0.76	Proficient
Data-based Decision Making	53	3.99	0.60	Proficient
Overall Data Literacy	53	3.92	0.63	Proficient

Level of Computational Thinking Skills of Secondary Science Teachers

Table 2 and Figure 1(b) present the domain-level means and standard deviations for computational thinking skills across all 53 respondents. All four dimensions were rated at the Proficient level. Decomposition registered the highest



Note. Dashed line marks the lower bound of the Proficient range (M = 3.41). Error bars represent SD.

Fig. 1. Domain-Level Means for (a) Data Literacy and (b) Computational Thinking Skills

mean (M = 3.92, SD = 0.73), followed by pattern recognition (M = 3.89, SD = 0.65), algorithmic thinking (M = 3.81, SD = 0.71) and abstraction (M = 3.75, SD = 0.70). The overall computational thinking skills mean (M = 3.84, SD = 0.64) places respondents within the Proficient level.

Table 2. Level of Computational Thinking Skills of Secondary Science Teachers

Domain	n	M	SD	Level
Decomposition	53	3.92	0.73	Proficient
Pattern Recognition	53	3.89	0.65	Proficient
Abstraction	53	3.75	0.70	Proficient
Algorithmic Thinking	53	3.81	0.71	Proficient
Overall Computational Thinking	53	3.84	0.64	Proficient

Difference Between Data Literacy and Computational Thinking Skills

The Shapiro-Wilk test of normality was conducted for all variables given the sample size (n = 53). Both variables violated the normality assumption, with data literacy showing W = 0.943, p = .014 and computational thinking skills showing W = 0.926, p = .003. Given these violations, the Wilcoxon Signed-Rank Test was employed as the appropriate non-parametric alternative. As shown in Table 3, the test revealed a statistically significant difference between the overall data literacy (M = 3.92) and computational thinking skills (M = 3.84) scores, W = 288.00, p = .040, r = 0.28.

Table 3. Wilcoxon Signed-Rank Test Comparing Data Literacy and Computational Thinking Skills

Comparison	Wilcoxon W	p-value	Effect Size (r)
DL vs. CT	288.00	.040	0.28 (Small)

Level of Data Literacy and Computational Thinking Skills Integration into Science Instruction

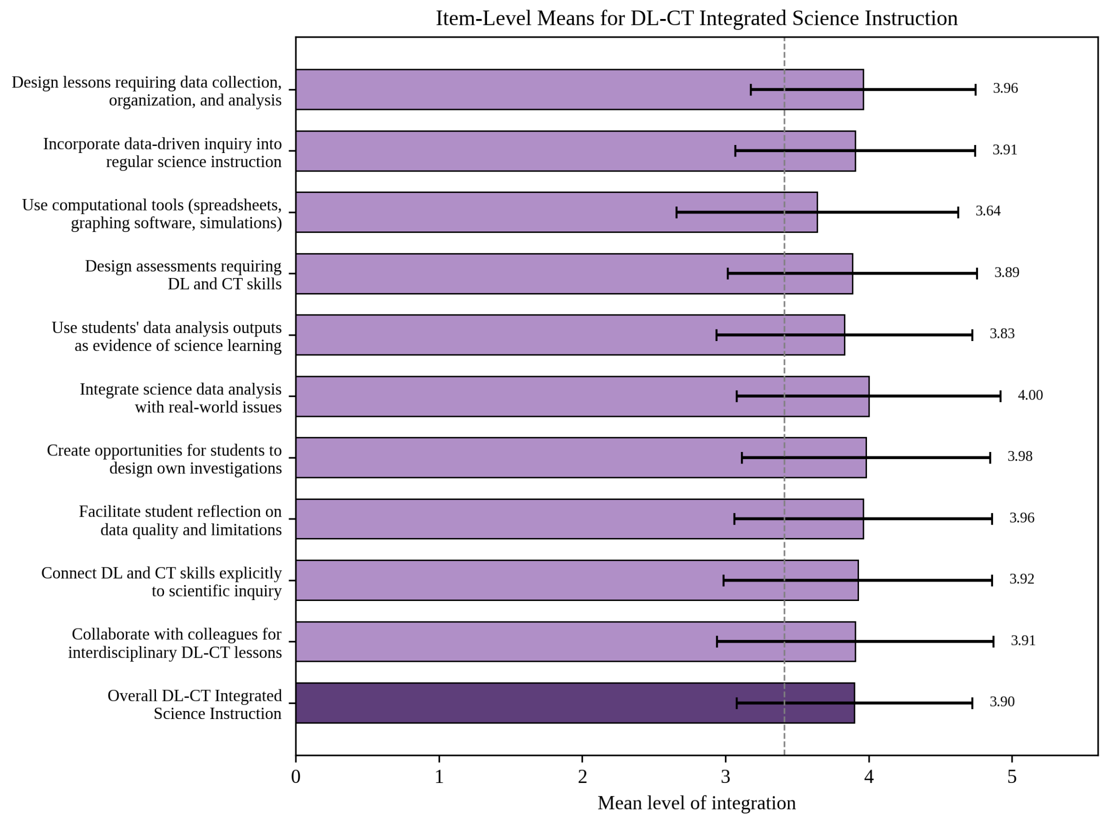
Table 4 and Figure 2 present item-level means for the DL-CT Integrated Science Instruction scale. The overall mean was M = 3.90 (SD = 0.82), placing it at the Highly Integrated level. The highest-rated item was integrating science data analysis with real-world issues (M = 4.00, SD = 0.92), while the lowest-rated item was the use of computational tools such as spreadsheets, graphing software and simulations in science lessons (M = 3.64, SD = 0.98).

Table 4. Level of Data Literacy and Computational Thinking Skills Integration into Science Instruction

Indicator	M	SD	Interpretation
Design lessons requiring data collection, organization, and analysis	3.96	0.78	Highly Integrated
Incorporate data-driven inquiry into regular science instruction	3.91	0.84	Highly Integrated
Use computational tools (spreadsheets, graphing software, simulations)	3.64	0.98	Highly Integrated
Design assessments requiring DL and CT skills	3.89	0.87	Highly Integrated
Use students' data analysis outputs as evidence of science learning	3.83	0.89	Highly Integrated
Integrate science data analysis with real-world issues	4.00	0.92	Highly Integrated
Create opportunities for students to design own investigations	3.98	0.87	Highly Integrated
Facilitate student reflection on data quality and limitations	3.96	0.90	Highly Integrated
Connect DL and CT skills explicitly to scientific inquiry	3.92	0.94	Highly Integrated
Collaborate with colleagues for interdisciplinary DL-CT lessons	3.91	0.97	Highly Integrated
Overall DL-CT Integrated Science Instruction	3.90	0.82	Highly Integrated

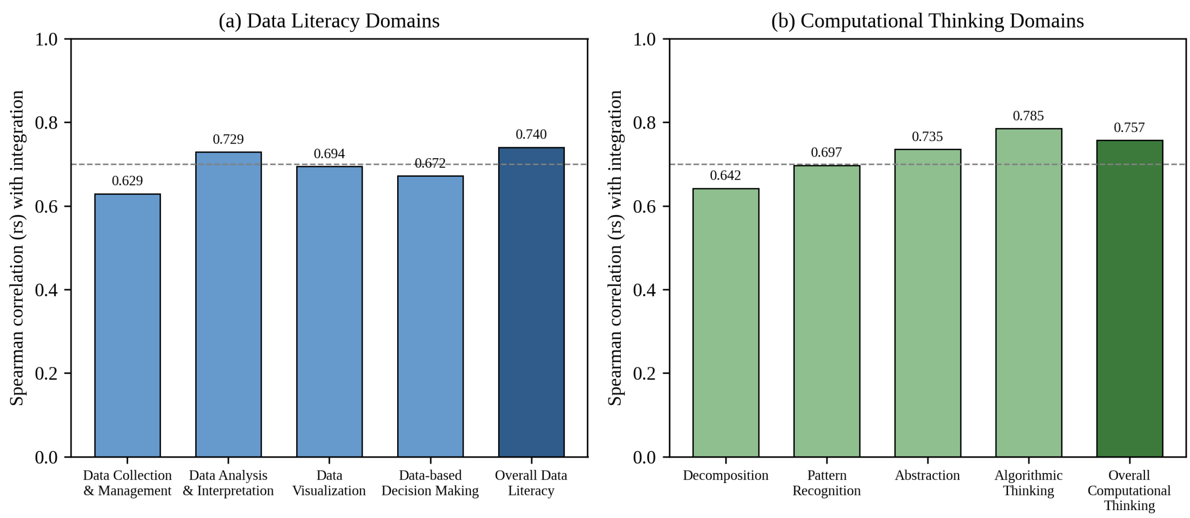
Correlation Between Data Literacy and Integrated Science Instruction

Spearman rank-order correlations were computed between all DL domains and the DL-CT integration score, given the violation of normality. As shown in Table 5, all four DL domains



Note. Dashed line marks the lower bound of the Highly Integrated range (M = 3.41). Error bars represent SD.

Fig. 2. Item-Level Means for DL-CT Integrated Science Instruction



Note. Dashed line marks the lower bound of a strong correlation (rs = .70). All correlations significant at p < .001.

Fig. 3. Spearman Correlations Between (a) Data Literacy Domains and (b) Computational Thinking Domains With DL-CT Integrated Science Instruction

showed statistically significant strong positive correlations with DL-CT integrated instruction. The overall correlation between data literacy and integration was rs = .740 (p < .001). At the domain level, data analysis and interpretation emerged as the strongest correlate (rs = .729), followed by data visualization (rs = .694), data-based decision making (rs = .672) and data collection and management (rs = .629).

Correlation Between Computational Thinking Skills and Integrated Science Instruction

As shown in Table 6 and Figure 3, all four CT domains showed statistically significant strong positive correlations with DL-CT integrated science instruction. Algorithmic thinking was the strongest correlate (rs = .785), followed by abstraction (rs = .735), pattern recognition (rs = .697) and decomposition (rs = .642). The overall CT-integration correlation was rs = .757 ($p < .001$).

Table 5. Spearman Correlation Between Data Literacy and DL-CT Integrated Science Instruction

DL Domain	Spearman rs	p-value	Interpretation
Data Collection and Management	.629	< .001	Moderate
Data Analysis and Interpretation	.729	< .001	Strong
Data Visualization	.694	< .001	Moderate
Data-based Decision Making	.672	< .001	Moderate
Overall Data Literacy	.740	< .001	Strong

Table 6. Spearman Correlation Between Computational Thinking Skills and DL-CT Integrated Science Instruction

CT Domain	Spearman rs	p-value	Interpretation
Decomposition	.642	< .001	Moderate
Pattern Recognition	.697	< .001	Moderate
Abstraction	.735	< .001	Strong
Algorithmic Thinking	.785	< .001	Strong
Overall CT Skills	.757	< .001	Strong

Discussion

The overall pattern of findings is broadly consistent with the study's guiding expectation, grounded in Constructivist theory and the Data Literacy and Computational Thinking frameworks, that secondary science teachers who possess stronger data literacy and computational thinking skills would also report stronger integration of these competencies into science instruction. The following sections discuss each set of findings in relation to prior research, consider their practical implications for science teaching and outline directions for further inquiry.

Data Literacy of Secondary Science Teachers

The finding that secondary science teachers demonstrated an overall self-assessed Proficient level of data literacy is broadly consistent with a growing body of literature. Pastore et al. (2025) found that most studies reported moderate to high data literacy levels among in-service teachers who had received structured professional development, a finding that aligns with the present results. Data-based decision making emerged as the highest-rated domain ($M = 3.986$), resonating with Mandinach and Schildkamp (2021), who argued that when teachers view data as actionable evidence for improving instruction, decision-making naturally becomes their most developed data literacy dimension. This is further supported by Sandoval-Ríos et al. (2025), who highlighted that structured training models emphasizing decision-making significantly produced teachers with the highest proficiency in translating data into instructional choices. In the context of science teaching, where teachers routinely interpret experimental results and student outputs, data-based decision making is arguably the most practiced competency (Amini & Sinaga, 2021).

Data visualization, however, registered the lowest mean ($M = 3.887$, $SD = 0.757$). This finding is consistent with Laramee (2023), who emphasized that visualization remains a cognitively complex and pedagogically challenging dimension. Fernandez Nieto et al. (2022) similarly noted that data visualization tasks can exceed the professional skill set of some educators. The relatively higher standard deviation for this domain further suggests greater variability in teacher competency, indicating uneven readiness across the sample.

However, the present results should be interpreted cautiously in light of the self-report methodology. Earlier studies employing performance-based measures have documented lower levels of data literacy among public school science teachers. Sandoval-Ríos et al. (2025) noted a persistent skills gap in data literacy training, particularly in developing-country contexts. The discrepancy between the present self-assessed proficiency and findings from performance-based studies may be attributable to social desirability bias inherent in self-report instruments, the professional development background of the participants or the institutional context within which the respondents operate. Future studies should incorporate objective, performance-based assessments to triangulate self-report findings.

From an implications standpoint, schools and teacher development programs should invest in visualization-specific professional development, particularly in graph literacy, infographic creation and the use of digital tools, to elevate this relatively weaker sub-domain (Wilkerson et al., 2025).

Computational Thinking Skills of Secondary Science Teachers

This finding is notable given the relatively recent introduction of CT into K-12 science education curricula and teacher professional development. The result is broadly supportive of emerging literature showing that teachers who have participated in CT-oriented professional development can reach proficiency across CT dimensions (Mumcu et al., 2023; Yadav et al., 2014). Decomposition registered the highest mean, suggesting that secondary science teachers are most adept at breaking complex science problems into manageable components, a finding that aligns with Mertens and Colunga (2025), who identified decomposition as the most cognitively accessible CT component for novice-to-intermediate learners.

Abstraction yielded the lowest mean ($M = 3.745$), a finding consistent with a substantial body of literature. Oser et al. (2025) concluded that abstraction remains the least proficiently developed CT skill in K-12 education. Asif et al. (2024) observed that deeper forms of abstraction remain challenging without dedicated professional learning, and Asif et al. (2023) found that teachers often simplify abstraction to merely ignoring details. Rodrigues et al. (2024) corroborated this by finding that abstraction sub-skills showed non-significant improvement in a semester-long CT intervention.

However, these findings partially contrast with Kong et al. (2020) and Rich et al. (2021), who reported that even after targeted professional development, many K-12 teachers continued to demonstrate inconsistent CT levels. The relatively higher self-assessed proficiency in the present study may reflect the specialized science background of the respondents, whose training in scientific modeling and systematic investigation provides a foundation overlapping with several CT dimensions. It is also possible that self-report inflation accounts for part of this discrepancy.

Abstraction and algorithmic thinking, as the lowest-scoring CT dimensions, should be the focus of targeted professional development. Abstraction benefits from structured, problem-based learning contexts where teachers are prompted to identify what is essential and what can be omitted in complex science scenarios. Algorithmic thinking development can be advanced through unplugged activities, flowcharting and lesson-plan design that requires teachers to sequence instructional steps explicitly (Tariq et al., 2025).

Difference Between Data Literacy and Computational Thinking Skills

The effect size (r = 0.28) falls within the small range according to Cohen's (1988) benchmarks (small = 0.10, medium = 0.30, large = 0.50), indicating that while the difference is statistically significant, its practical magnitude is modest. It should be noted that comparing means across two different constructs measured by different instruments carries inherent conceptual limitations. Data literacy and computational thinking are distinct constructs, and a mean difference does not necessarily indicate that teachers are more capable in one than the other in an absolute sense. The comparison is meaningful primarily as a relative indicator of perceived proficiency and as a guide for prioritizing professional development resources.

This finding reflects an asymmetry in the depth of secondary science teachers' professional preparation. Science teachers' professional formation has historically embedded data collection, analysis and interpretation as core competencies within laboratory practices, scientific inquiry cycles and assessment literacy frameworks. Computational thinking, by contrast, is a comparatively newer curricular expectation, and its formal integration into teacher education programs and K-12 science curricula is still emergent (Bocconi et al., 2022; Yadav et al., 2014). This finding is supported by Hsu et al. (2024), who documented that despite growing momentum, there remains a notable absence of consensus on how to assess and build teachers' CT knowledge. The Philippine context, where CT integration into science education is still at an early curriculum stage, may explain the observed gap. This has direct policy implications, as the K-12 curriculum framework in the Philippines could benefit from a more explicit articulation of CT expectations within science learning competencies, supported by targeted CT professional development for in-service teachers.

Integration of Data Literacy and Computational Thinking Skills into Instruction

The finding that secondary science teachers rated their DL-CT integrated science instruction at a Highly Integrated level suggests that these teachers perceive themselves as having moved beyond surface-level familiarity with both skill sets and as embedding both meaningfully into their instructional practice. Their highest-rated capability, integrating science data analysis with real-world issues, reflects a pedagogical orientation aligned with authentic and context-driven science learning. This result is consistent with Coenraad et al. (2022), who found that the most successful integration sites were those connected to authentic data analysis tasks in real-world contexts, and with Moon et al. (2023), who observed stronger instructional coherence among teachers integrating CT through problem-based science tasks.

However, the lowest-rated item, the use of computational tools, warrants careful attention. This result echoes the UNESCO Global Education Monitoring Report (2023), which documented limited digital tool use in science classrooms even in high-income countries. In the Philippine secondary school setting, limited access to computers, software licenses and reliable internet connectivity may constitute structural barriers to computational tool use, a concern highlighted by Kadioglu-Akbulut et al. (2023). Angeli et al. (2016) cautioned that pedagogical integration of computational tools requires dedicated institutional support, including infrastructure provisioning, technical assistance and subject-specific training. The gap between conceptual and tool-mediated integration reinforces Lim et al. (2023), who found that technology-tool integration lagged behind despite strong CT beliefs and pedagogical knowledge.

School administrators and curriculum planners should therefore distinguish between conceptual DL-CT integration, where teachers show strong self-assessed performance, and technology-tool-mediated CT integration, where a meaningful gap persists. Resource allocation, laboratory provisioning and professional development should prioritize the latter.

Relationships Between Competencies and Integrated Instruction

This affirms the theoretical proposition that data literacy is a foundational component of integrated science instruction. This finding is strongly supported by Mandinach and Schildkamp (2021), who argued that data-literate teachers are significantly more likely to design, implement and assess inquiry-based lessons. This pattern is consistent with research on teachers' instructional data use, which has consistently identified analytical and interpretative skills, rather than data collection skills, as the critical bridge between data literacy and instructional action (Filderman et al., 2022; Pastore et al., 2025). The moderate-to-strong correlation for data visualization is consistent with Wilkerson et al. (2025), who found that teachers with higher visualization literacy were more effective in facilitating student-centered data visualization discussions. These findings extend the TPACK-integrated data literacy framework of Cui and Zhang (2022), providing empirical support for the proposition that data literacy is not merely an administrative competency but a pedagogically active one that shapes instructional design.

The overall CT-integration correlation (rs = .757) was marginally higher than the DL-integration correlation (rs = .740). However, it is important to note that the difference of .017 is small, and a formal test for comparing dependent correlations, such as Steiger's Z-test, was not conducted. Therefore, it cannot be concluded with statistical confidence that computational thinking is a significantly stronger correlate of integration than data literacy. The pattern is nonetheless suggestive in nature and warrants further investigation. This observation is broadly consistent with Yadav et al. (2014), who argued that CT, when appropriately adapted for science classrooms, provides the procedural and structural scaffolding through which data literacy practices are operationalized in instruction.

Algorithmic thinking emerged as the single strongest correlate among all CT and DL domains (rs = .785). Algorithmic thinking, defined as the ability to design logical and sequential procedures for solving complex problems, maps directly onto lesson planning, procedural scaffolding and scientific inquiry design. Teachers who think algorithmically may be more inclined to design structured investigations, explicit data analysis protocols and scaffolded argumentation sequences, all of which are hallmarks of integrated DL-CT science instruction (Mumcu et al., 2023).

These results are broadly consistent with the integrated STEM-CT literature reviewed by Tariq et al. (2025), which emphasized that CT integration in science teaching is most successful when teachers deploy all four CT domains in concert rather than in isolation. It should be emphasized, however, that correlation does not establish causation. Future studies employing regression analysis or structural equation modeling would be needed to determine whether computational thinking skills, data literacy or their combination serve as significant predictors of instructional integration.

A further methodological consideration is the potential for common method variance, given that all three variables were assessed through self-report instruments completed by the same respondents at the same time. This shared method may artificially inflate the observed correlations. Future research should employ multi-method designs, such as combining self-report surveys with classroom observation protocols or performance-based assessments, to mitigate this threat.

Conclusions

Secondary science teachers demonstrated self-assessed Proficient levels in both data literacy and computational thinking skills, with all sub-domains falling within the same proficiency band. A statistically significant difference was found between the two skill sets, indicating that teachers perceive data literacy as a slightly stronger area of competence than computational thinking, a pattern reflecting the longer curricular history of data practices in science education relative to the more recently introduced CT competencies. Within data literacy, data-based decision making was the strongest domain, while data visualization was the weakest, with the latter showing greater variability in teachers' graphical and visual data representation skills. Within computational thinking, decomposition was the highest-rated dimension, while abstraction was the lowest, consistent with literature identifying abstraction as the most cognitively demanding and least developed CT skill among K-12 educators. Teachers rated their DL-CT integrated science instruction at a Highly Integrated level, with real-world data contextualization rated highest and use of computational tools rated lowest, pointing to a structural gap between conceptual integration and technology-mediated instruction. Both data literacy and computational thinking showed strong positive correlations with integrated instruction. Algorithmic thinking emerged as the single strongest correlate across all domains. While the CT-integration correlation was marginally higher than the DL-integration correlation, this difference was small and was not formally tested for statistical significance. Both skill sets appear to play substantial and complementary roles in supporting integrated instructional practice.

Limitations

Several limitations of this study should be acknowledged. First, the reliance on self-report instruments introduces the possibility of social desirability bias and response inflation, meaning that teachers may perceive and report higher competence than what objective, performance-based measures would reveal. Second, the modest sample size (n = 53) drawn from a single province through purposive sampling limits the generalizability of the findings. Third, the cross-sectional design precludes causal inference; the observed correlations cannot be interpreted as evidence of causal relationships.

Recommendations

Based on the findings and limitations of this study, the following recommendations are offered. Schools and teacher development programs should design targeted interventions addressing the two weakest sub-domains identified, namely abstraction within computational thinking and data visualization within data literacy. For abstraction, structured problem-based tasks that require teachers to identify essential features, suppress irrelevant detail and build generalizable models should be incorporated into professional learning. For data visualization, training focused on graph literacy, infographic creation and the pedagogical use of digital visualization tools should be embedded into science-specific professional development.

Given the lowest integration rating for computational tool use, school administrators should differentiate between conceptual DL-CT integration, where teachers demonstrate strong self-assessed performance, and technology-tool-mediated CT integration, where a meaningful gap persists. Resource allocation should prioritize hardware provisioning, software licensing and subject-specific training to ensure that science teachers can confidently deploy spreadsheets, graphing software and simulations as computational tools in inquiry-based lessons.

Curriculum planners and teacher educators should treat computational thinking as a co-equal priority alongside data literacy. The Philippine K-12 science curriculum framework should articulate explicit, progressive CT learning competencies covering all four dimensions across grade levels. Pre-service science education programs should incorporate both data literacy and computational thinking as core, assessable content in science methods courses.

Given the strong correlation between algorithmic thinking and integrated science instruction, professional development that builds teachers' capacity to sequence instruction explicitly, design structured investigations and scaffold data analysis is recommended. Unplugged activities, flowcharting and explicit lesson-design training aligned with scientific inquiry processes are suggested entry points.

Finally, future research should address the limitations identified in this study. Longitudinal or experimental designs should be employed to test whether targeted DL and CT professional development produces measurable improvements in instructional quality. Performance-based measures, classroom observation protocols and student outcome data should be incorporated to complement self-report findings. Factor analytic studies of the instruments are recommended to establish construct validity. Larger, probability-based samples from multiple provinces should be used to enhance generalizability. Additionally, regression or structural equation modeling approaches should be employed to determine whether data literacy and computational thinking serve as significant predictors of instructional integration.

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Ethics Approval

This study did not require review by a formal institutional ethics or review board. As the respondents were public school teachers rather than students or another vulnerable population, and the study posed no more than minimal risk, formal ethics committee approval was not required under the applicable Philippine research regulations. Ethical clearance was instead secured through an official permission letter from the Department of Education Masbate Division Office, and the study adhered to standard ethical safeguards throughout, including an informed consent prior to participation, voluntary participation with the right to withdraw at any time and compliance with Republic Act No. 10173, the Data Privacy Act of 2012 of the Philippines.

Data Availability Statement

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

AI Disclosure Statement

The authors declare that artificial intelligence (AI) tools were used in language polishing. All aspects of the research, including data collection, analyses, interpretation and manuscript preparation, were carried out entirely by the authors without the assistance of AI-based technologies.

Conflict of interest

The authors declare no conflict of interest.

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Грамотність у роботі з даними та обчислювальне мислення вчителів природничих дисциплін середньої школи: кількісне дослідження рівнів, відмінностей та інтеграції у навчальний процес

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Авторський вклад: A – дизайн дослідження; B – збір даних; C – статаналіз; D – підготовка рукопису; E – збір коштів

Реферат. Стаття: 12 с., 6 табл., 3 рис., 38 джерел

Мета. У дослідженні вивчено рівні грамотності у роботі з даними (DL) та навичок обчислювального мислення (CT) серед учителів природничих дисциплін середньої школи, ступінь їх інтеграції у викладання природничих дисциплін, а також взаємозв'язки між цими компетентностями та їх інтеграцією у навчальний процес.

Матеріали та методи. У дослідженні описово-кореляційного дизайну взяли участь 53 учителі природничих дисциплін середніх шкіл провінції Масбате, Філіппіни. Учасники заповнили три розроблені авторами інструменти типу шкали Лайкерта для оцінювання DL, CT та інтеграції DL-CT у викладання природничих дисциплін. Дані аналізували за допомогою середніх значень і стандартних відхилень, критерію знакових рангів Вілкоксона та рангової кореляції Спірмена.

Результати. Учителі оцінили свій рівень як компетентний щодо DL ($M = 3,92$; $SD = 0,63$) і CT ($M = 3,84$; $SD = 0,64$); різниця між цими показниками була статистично значущою ($W = 288,00$; $p = 0,040$; $r = 0,28$). Учителі повідомили про високий рівень інтеграції DL-CT у навчальний процес ($M = 3,90$; $SD = 0,82$). Кореляційний аналіз Спірмена виявив сильні позитивні зв'язки інтеграції як із DL ($r_s = 0,740$), так і з CT ($r_s = 0,757$), в обох випадках $p < 0,001$. Алгоритмічне мислення мало найсильніший окремий зв'язок з інтеграцією ($r_s = 0,785$).

Висновки. Учителі природничих дисциплін середньої школи продемонстрували компетентний, але неоднорідний рівень грамотності у роботі з даними та обчислювального мислення, при цьому відносно слабшими аспектами були абстрагування та доступ до обчислювальних інструментів. Обидві компетентності відіграють суттєву та взаємодоповнювальну роль в інтегрованому викладанні природничих дисциплін. Рекомендовано цільове професійне вдосконалення, спрямоване на розвиток виявлених слабших аспектів.

Ключові слова: грамотність у роботі з даними, обчислювальне мислення, природнича освіта, інтеграція у навчальний процес, учителі середньої школи.

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