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IJSET

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International Journal of Science Education and Teaching (IJSET) is supported by Science Education Association (Thailand) or SEAT. IJSET seeks articles addressing issues including science education, physics education, chemistry education, biology education, technology education, STEM education, science teacher education, early childhood science education, science curriculum and instruction, and other related science educational fields.

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IJSET welcomes original research articles, academic articles, and review articles covering a broad spectrum of topics, including physics, chemistry, biology, technology education, STEM education, science teacher education, early childhood science education, science curriculum and instruction, and other related fields of science education. As an open-access journal, IJSET does not charge article processing charges (APCs) or publication fees, ensuring that quality research remains freely accessible to both authors and readers.

To maintain the highest standards of scholarly publishing, all submitted manuscripts undergo a rigorous double-blind peer-review process conducted by qualified reviewers. Authors are expected to uphold the principles of research integrity by providing accurate citations, complying with applicable research ethics requirements, and transparently disclosing the use of artificial intelligence (AI) tools in conducting research or preparing manuscripts. We also encourage authors to cite only relevant and reliable scholarly sources and to carefully verify all references.

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On behalf of the Editorial Board, I would like to express our sincere appreciation to our authors, reviewers, and editors for their valuable contributions and dedication. We hope that the articles published in this issue will stimulate further research, encourage international collaboration, and contribute to the continued advancement of science education and teaching.



Associate Professor Dr. Saksri Supasorn

Editor-in-Chief

International Journal of Science Education and Teaching (IJSET)

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Effects of the VIMCC (Visual, Interactive, and Meaning-Centered Conceptualization) Approach on Students' Conceptual Understanding, Learning Engagement, and Insights in Subatomic Particles

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Abstract. This action research focused on improving Grade 8 students' performance in differentiating subatomic particles by strengthening their conceptual understanding of atomic structure through the VIMCC (Visual, Interactive, and Meaning-Centered Conceptualization) approach. The study was conducted in a public high school in Leyte, Philippines, among selected Grade 8 students who had difficulty differentiating subatomic particles. Initial observations and pre-test results revealed that students had weak prior knowledge of atomic structure, which affected their understanding of subatomic particles. To address this problem, the researchers implemented the VIMCC Approach embedded in a 7E's lesson plan. This approach integrated Visual tools (YouTube video presentations, color-coded learning materials, and 3D atomic models), Interactive activities (game-based matching task and model manipulation), and Meaning-Centered strategies (concept maps and the Frayer Model). The study employed participatory action research using formative assessments, classroom observations, and focus group discussions as data sources. Results showed significant improvements in students' conceptual understanding and academic performance, with increasing post-test mean percentage scores in both Cycle 1 and 2. Normalized gain scores and paired t-test results indicated positive learning gains in both cycles. Observations revealed high levels of effort and initiative, accompanied by low levels of disruptive and inattentive behaviors. Focus group discussions further revealed that students perceived the VIMCC-based activities as enjoyable, engaging, easier to understand, and more interesting. The findings highlight the effectiveness of the VIMCC Approach in strengthening secondary students' conceptual understanding of atomic structure, thereby improving their ability to distinguish among subatomic particles and enhancing their confidence in learning science.

Keywords: conceptual understanding; atomic structure; subatomic particles; VIMCC approach; action research

INTRODUCTION

Background and Importance of Subatomic Particles

Subatomic particles—protons, neutrons, and electrons—are the fundamental building blocks of atoms that determine an element's identity, stability, and reactivity. In science education, mastering

these particles are essential for understanding core chemistry topics such as atomic structure, chemical bonding, the periodic table, and chemical reactions. Under the Philippine MATATAG Curriculum, students are expected to develop scientific reasoning and problem-solving skills by exploring how these particles function and applying this knowledge to real-world contexts (Department of Education, 2023). These competencies prioritize conceptual understanding over rote memorization. It directly aligns with the spiral progression approach mandated by Republic Act No. 10533, ensuring that foundational concepts are securely mastered before students advance to more complex chemical principles in higher grade levels. A clear understanding of subatomic particles is also essential in developing students' scientific reasoning and problem-solving skills. Understanding how protons, neutrons, and electrons interact helps students apply scientific concepts to the real world.

Learning Challenges and Performance Gaps in Subatomic Particles

However, at the research site, the researchers observed that students continued to experience significant learning difficulties with this topic. Many students continued to struggle with subatomic particles due to the topic's abstract and highly conceptual nature, which often leads to misconceptions and weak academic performance (Kaya, 2023; Fitriza & Gazali, 2018). Classroom observations, learner interviews, and analysis of student outputs revealed that many learners struggled to accurately identify and explain the mass, charge, symbol, and location of subatomic particles.

Empirical findings in chemistry education further indicate that a weak understanding of atomic structure hinders learning later topics like bonding and reactions. Without a solid grounding in atomic theory and atomic model, students develop fragmented knowledge and rely on memorization rather than conceptual understanding (Dela Cruz et al., 2025; Fitriza & Gazali, 2018). As a result, students may recall factual information but fail to explain why chemical phenomena occur, limiting their ability to apply concepts in problem-solving and real-life situations. In particular, the 2022 Programme for International Student Assessment (PISA) and the 2024 National Achievement Test reported below-average performance, highlighting ongoing challenges in improving scientific literacy within the Philippine education system (Organisation for Economic Co-operation and Development, 2023; Second Congressional Commission on Education (EDCOM) II, 2024).

To systematically examine these learning difficulties, a problem analysis was conducted. This structured process maps a core problem, its causes, and its effects (UNECA, n.d., Chapter 8), providing a basis for designing targeted interventions by identifying root causes (Debesa, 2025). To operationalize this process, with participants' consent, the researchers used meta-cards and follow-up questions to identify learning difficulties. These issues were organized into a problem tree (see **Figure 1**) to map hierarchical causes and effects, highlighting the most influential and addressable factors. Through this analysis with struggling learners, the core problem emerged: students' poor performance in differentiating among subatomic particles. The difficulty may stem from the abstract and unobservable nature of submicroscopic concepts, requiring students to rely on mental visualization, which can hinder their understanding and lead to misconceptions (Laohapornchaiphan & Chenprakhon, 2024; Susilaningasih & Aprilia, 2022). Despite inquiry-based learning, students still struggle with subatomic particles in terms of student motivation, suggesting that improving their confidence may require additional strategies beyond content mastery (Azizoğlu, 2022). This main problem was split into three key sub-problems: (1) lack of conceptual understanding of atomic structure, (2) poor skills in identifying subatomic particles, and (3) lack of interest (see Figure 1). Researchers prioritized the first branch—lack of conceptual understanding—because it serves as a prerequisite for mastering subatomic particles and heavily influences a student's ability to interpret atomic models, relate particle properties, and apply scientific reasoning. Studies show that the misconceptions and lack of comprehension of this topic are due to limited prior knowledge leading to poor understanding of subatomic particles (Jusgado, 2024). More importantly, this cause was

considered the most feasible and manageable to address through classroom-based instructional interventions and available data sources.

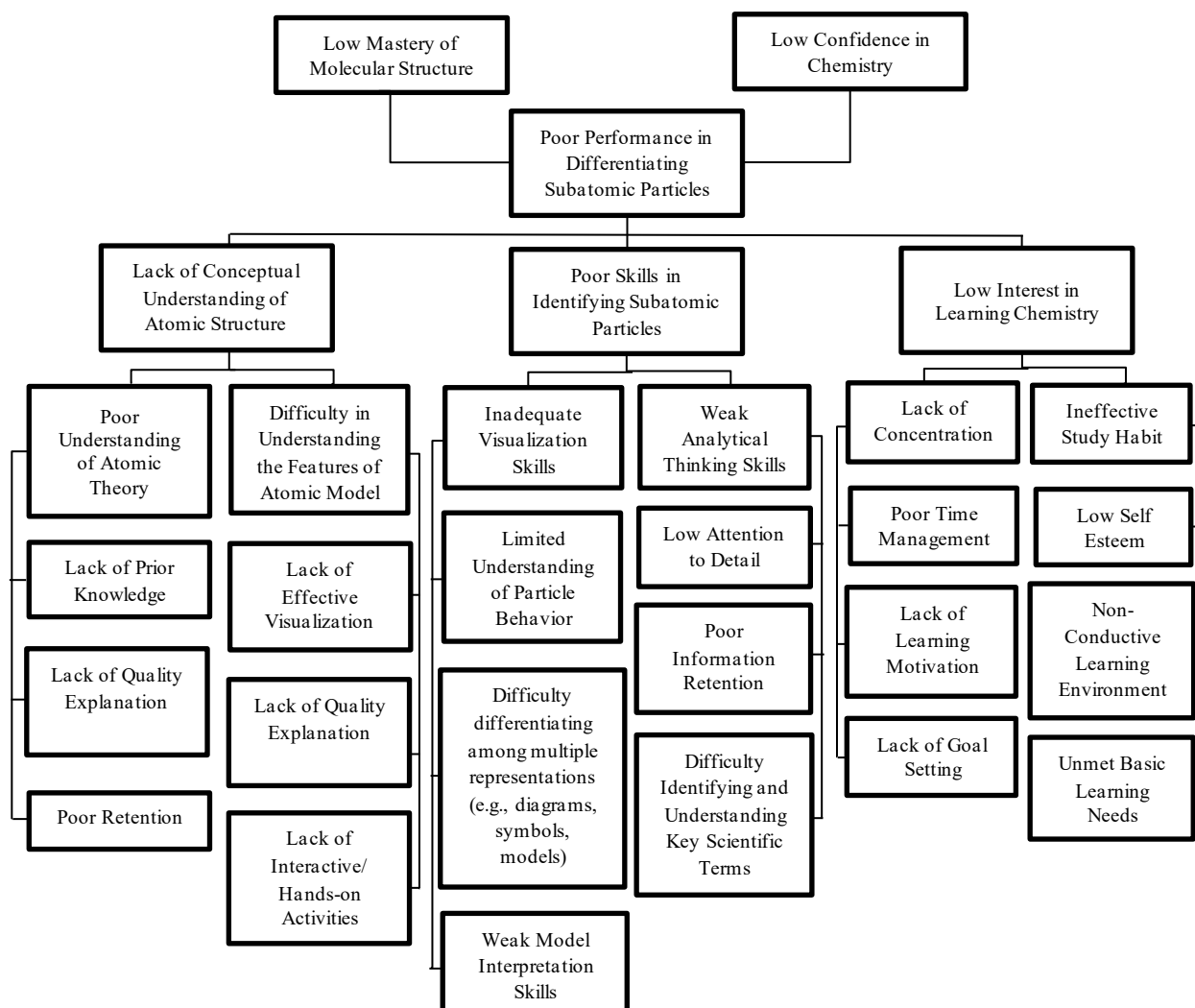


Figure 1: Problem Tree

Instructional Intervention

Stronger conceptual learning correlates directly with advanced scientific reasoning, providing a logical framework for problem-solving while driving behavioral and academic growth (Bautista, 2024). To address conceptual gaps regarding subatomic particles, the researchers implemented the VIMCC (Visual, Interactive, and Meaning-Centered Conceptualization) approach. Because atomic structure exists at an abstract, submicroscopic level and cannot be directly observed, this combined strategy engages learners through seeing, doing, and making sense of ideas, preventing rote memorization and misconceptions.

Visual-based strategies present concepts in clear, structured forms to help students organize and retain information. For example, concept maps visually display relationships between ideas to support deeper understanding, memory, and critical thinking. Concept mapping enhances knowledge representation by allowing learners to actively connect new information with prior knowledge (Narang & Lata, 2024). Similarly, video presentation was used to introduce concepts through animations, images, and guided explanations, supporting student engagement and comprehension. Video-supported discovery learning can promote active participation and improve understanding in

science classes (Koto, 2020). Additionally, 3D models let students observe atomic structures from multiple perspectives to make abstract ideas concrete, while color-coded materials highlighted patterns and categories. The role of visual design in strengthening memory retention and comprehension, ensuring that learning experiences are both engaging and conceptually rich.

Interactive interventions encouraged active student involvement and experiential learning. A key activity was the Atomic Model Matching Game, a game-based classroom task requiring real-time matching and problem-solving. This approach aligns with the findings of Pacturan et al. (2024), who reported that gamification can enhance academic performance and inform more responsive teaching strategies. The use of 3D models also served an interactive function, as students could manipulate and explore the models hands-on, enabling them to better grasp spatial relationships and structural features of atomic components (Astuti, 2020).

Meaning-centered interventions focus on developing a deep and lasting understanding rather than simple memorization. The Frayer Model strategy guided students in defining key concepts, identifying their characteristics, and providing examples and non-examples. Sacapaño and de Castro (2022) found that this approach significantly improves secondary learners' science vocabulary and conceptual clarity. Concept maps further supported this process by encouraging students to link related ideas in meaningful ways, reinforcing the cognitive benefits identified by Narang & Lata (2024).

By synthesizing these possible interventions, the researchers developed an integrative, unified approach termed the VIMCC (Visual, Interactive, and Meaning-Centered Conceptualization). The combination of visual, interactive, and meaning-centered interventions was intentionally designed to address the different challenges associated with learning subatomic particles. Visual strategies helped students see or visualize the concepts, interactive strategies allowed them to experience and explore the concepts, and meaning-centered strategies enabled them to understand and internalize the concepts. Together, these approaches created a complementary learning process that supported conceptual understanding, reduced misconceptions, increased engagement, and promoted meaningful science learning.

Theoretical Foundations

Effective interventions for teaching atomic structure require a strong theoretical basis. This study utilizes the VIMCC approach, which draws on established learning theories to support students' conceptual understanding, with each component grounded in specific educational frameworks.

The visual component of VIMCC uses diagrams, models, and illustrations to help students grasp complex concepts, a strategy strongly supported by Allan Paivio's Dual Coding Theory. By processing information through both verbal and visual channels, students recognize patterns and structures that text alone cannot reveal, leading to deeper conceptual understanding (Paivio, 1986). This is further backed by Richard E. Mayer's Multimedia Learning Principles, which state that learners understand concepts better when words and visuals are presented together rather than separately (Mayer, 2021). Additionally, John Sweller's Cognitive Load Theory highlights that integrating visuals with clear explanations minimizes extraneous cognitive load, allowing students to process complex topics like atomic structure more efficiently.

The interactive component of the VIMCC Approach actively engages students through collaboration, discussion, and hands-on activities. This element is underpinned by Lev Vygotsky's Sociocultural Theory, which emphasizes that social interaction and guided instruction within the Zone of Proximal Development (ZPD) allow students and teachers to co-construct knowledge for better retention. Complementing this, progressivist educational philosophy emphasizes "learning by doing." These interactive, hands-on experiences promote critical thinking and active participation, enabling students to engage meaningfully with scientific concepts rather than passively receiving information.

The meaning-centered component ensures a solid conceptual foundation by connecting new information to prior knowledge and essential scientific terms. Bartlett's Schema Theory highlights how learners organize and retain new information by linking it to existing schemas, making

comprehension faster and more meaningful (Bartlett, 1932; Iran-Nejad & Winsler, 2000). This is complemented by the essentialist philosophy, which emphasizes the accurate understanding of key concepts, helping students reduce misconceptions and grasp the fundamental principles of atomic structure (Bagley, 1938).

By integrating visual representations, interactive engagement, and meaning-centered learning, the VIMCC approach enables students to understand atomic structure more deeply and accurately. This framework aligns with Multimodal Learning Theory, which emphasizes that learning is enhanced when students process information through multiple modes like visual, verbal, and kinesthetic experiences (Mayer, 2021). It also reflects Constructivist Theory, where learning is an active process of constructing knowledge through meaningful interactions with materials, peers, and prior experiences (Piaget, 1952; Vygotsky, 1978). Together, these foundations create a cohesive framework that fosters an engaging, supportive environment to improve science education.

RESEARCH QUESTIONS

This study aims to answer the central question: How does enhancing Grade 8 students' conceptual understanding of atomic structure in public schools improve their ability to differentiate subatomic particles using the VIMCC Approach?

Specifically, this study seeks to answer the following questions:

1. To what extent does the VIMCC approach improve students' conceptual understanding, as indicated by the difference between pre-test and post-test results?
2. What is the level of students' engagement when the VIMCC approach is implemented as an intervention?
3. What insights do students gain regarding how the VIMCC approach facilitated their understanding of atomic structure?

METHODOLOGY

PAR Cycle

The researchers conducted the study using the participatory action research (PAR) method. Participatory Action Research (PAR) was a cyclical approach involving planning, action, observation, and reflection (Kendon et al., 2007). PAR improved learning by enabling ongoing adjustments based on effective strategies and stood out by actively involving participants as partners rather than treating them only as research subjects (Feekery, 2023).

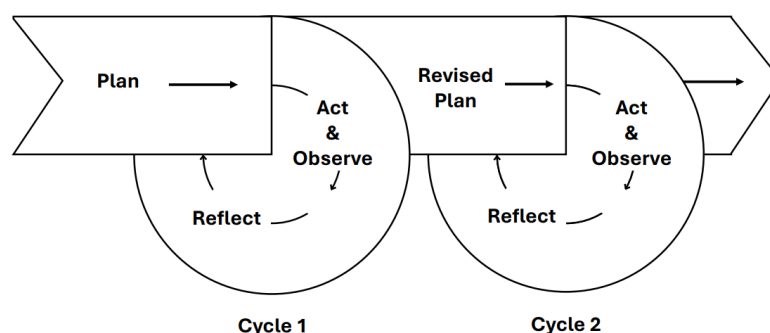


Figure 2: Steps of the Action Research Process

- (1) Planning Phase - Through problem analysis, the researchers identified the learning challenges of struggling Grade 8 students using meta-cards, follow-up questions, and thematic grouping. They mapped these issues into a cause-and-effect problem tree, which was then translated into an objective tree to define clear goals. These goals guided the development of targeted lesson plans, which three science teachers validated before implementation.

- (2) Action Phase - Researchers collaborated with students, parents, administrators, and teachers to implement the interventions. After securing parental consent, students attended an orientation and participated in a two-session, hour-long remedial program during Cycle 1. Following a pre-test, lessons covered Atomic Theory on Day 1 and Atomic Models on Day 2, with student engagement monitored using the SEOC checklist. Finally, a focus group discussion gathered student insights, a post-test assessed learning gains, and participants received tokens of appreciation.
- (3) Observation Phase - During the instructional process, one researcher served as the demonstration teacher, acted as observers to ensure objective monitoring—one handling documentation—and another functioned as a class facilitator to support students.
- (4) Reflection Phase - The researchers analyzed assessment results, classroom observations, and FGD responses to evaluate the effectiveness, long-term viability, and to identify possible learning gaps of the VIMCC Approach.

This process unfolds across two cyclical phases (**Figure 2**). In Cycle 2, the researchers used findings and limitations from Cycle 1 to refine the interventions. These revised strategies were implemented with the same Grade 8 participants across two sessions using the 7Es model (see **Table 2**), incorporating formative reviews, physical demonstrations, guided visuals, and structured group work (see **Table 6**). Data collection mirrored Cycle 1, utilizing pre- and post-tests, quizzes, the SEOC checklist, and a Focus Group Discussion (FGD) alongside lesson observations to monitor engagement and gather student feedback.

Research Locale

This study was conducted at Baybay National High School, a public secondary school located in Baybay City, Leyte, Philippines, during the first quarter of the Academic Year 2025–2026. The participants were Grade 8 students enrolled in the school during the same academic year.

Participants

Participants were selected through purposive sampling based on their first-quarter Science 7 scores on the phases of matter. With the adviser's consent and guidance, the scores were used to identify struggling learners scoring 70% or below. Thirteen Grade 8 students were initially selected; however, only 8 students participated in the study, as the remaining students were not permitted by their parents to take part. These selected students then received the interventions from the researchers.

The participants of the study were assessed using the Student Engagement Observation Checklist (SEOC) by the four researchers, none of whom were the participants' science teachers, thereby minimizing observer bias. Before conducting the observations, the researchers were oriented on the purpose, indicators, and proper use of the SEOC to ensure consistent and objective implementation throughout the study.

Research Tools

The study employed a variety of research tools to gather data on students' academic performance, engagement, and perceptions of the intervention. These included pre-tests, post-tests, quizzes, the Students' Engagement Observation Checklist (SEOC), and Focus Group Discussions (FGD), as shown in **Table 1**.

Table 1: Research Instruments Used

Tools	Description	Purpose
Pre-test/Post-test	20- item multiple - choice test on subatomic particle differentiation	Measure conceptual understanding gains
Formative Assessments (Session Quizzes)	10- item MCQs after each 7Es Lesson Plan	Assess immediate learning from VIMCC activities
SEOC Checklist	18-item observation scale (1-5: effort, initiative, disruptive, inattentive)	Document behavioral engagement patterns
FGD Guide	7 open-ended questions on intervention experiences	Gather qualitative student reflections

To ensure content validity, the pre-test, post-test, and quizzes were reviewed by three master science teachers with over 5 years of experience. They evaluated the items for clarity, appropriateness, and exact alignment with Grade 8 learning competencies, and revisions were made based on their feedback. Reliability was supported through item review. Daily short quizzes monitored students' developing conceptual understanding. Because intervention components varied by session (see **Table 2**), these quiz results reflect snapshots of understanding for that day's concepts, providing evidence of student progress to help explain the differences between the pre-test and post-test.

Table 2: 7Es Lesson Plans for Day 1 and 2

7Es Step	Day 1		Day 2	
	Lesson: Atomic Theory	Description	Lesson: Atomic Model	Description
Elicit	Application of Concept Map ^{a,c}	Match phrase strips and identify characteristics of states of matter using a concept map.	Atom Drawing Reflection	Review and explain previous atom drawings.
Engage	Activity: What's inside?	Observe and guess the contents of an object to introduce atomic structure.	Activity: Guess the Scientist Riddle	Solve riddles to identify scientists and their contributions.
Explore	Activity: Which Theory came First?	Arrange atomic theories in chronological order.	Gamified Classroom Activity: Atomic Model Matching Game ^b	Match scientists, models, and images in a group game.
Explain	Multimedia Presentation: YouTube Video ^a	Watch a video on the development of atomic theory to strengthen initial understanding and respond to the accompanying guide questions.	Utilization of 3D Model ^{a,b}	Observe and manipulate 3D atomic models.
Elaborate	Color-Coded Learning Materials ^a	Arrange and group color-coded cards of atomic theories.	Frayer Model Strategy ^c	Define and describe subatomic particles, including their characteristics, examples, and non-examples.
Evaluate	Short Quiz	Answer questions about atomic theory.	Short Quiz	Answer questions about subatomic particles and models.
Extend	Draw an atom	Draw and label the parts of an atom.		

Intervention Legend: *a* = Visual Interventions; *b* = Interactive strategies; *c* = Meaning-Centered strategies

The SEOC tool, a validated checklist adopted from Cassar & Jang (2010), was used to assess students' engagement using a 5-point Likert scale (1 – Never, 2 – Rarely, 3 – Sometimes, 4 – Often, 5 – Always). The checklist included indicators under four subscales: Effort (E), Initiative (I), Disruptive Behavior (D), and Inattentive Behavior (N). Effort refers to persistence and task completion. Initiative reflects active participation and willingness to engage. Disruptive behavior includes actions that interrupt learning. Inattentive behavior refers to lack of focus or withdrawal during class activities.

Lastly, Focus Group Discussions (FGD) were conducted using an expert-reviewed, standardized protocol to gather students' experiences. The guide questions were focused on their learning, helpful

activities, difficulties, and interest in science. Responses were recorded, transcribed, and analyzed to identify common themes. The following were the guide questions used for the FGD.

1. Throughout the implementation process, can you describe your overall experience with the 6 interventions used?

2. Do you believe that the interventions applied enhanced your learning experience compared to the traditional teaching methods? If yes, in what way and what specific intervention/s? If not, explain why.

3. Can you share what specific intervention/s that were applied that helped deepen your understanding of subatomic particles? What made it effective for you?

4. Were there any difficulties or challenges you faced during the implementation, and how did those experiences contribute to your overall learning process?

5. What was your initial understanding of subatomic particles before the intervention, and how did it change after?

6. In your opinion, what is the most intriguing about the ideas of subatomic particles that inspired you to participate?

7. Throughout each activity, do you find the topic of subatomic particles more interesting? If yes, what made you want to learn more about this topic? If not, why not?

Data Collection

Data collection followed a triangulation approach, combining formative assessments (pre/post-tests, quizzes), classroom observations (SEOC), and Focus Group Discussions (FGDs) to validate findings and minimize bias. The researcher collected the data according to the following steps in figure 3.

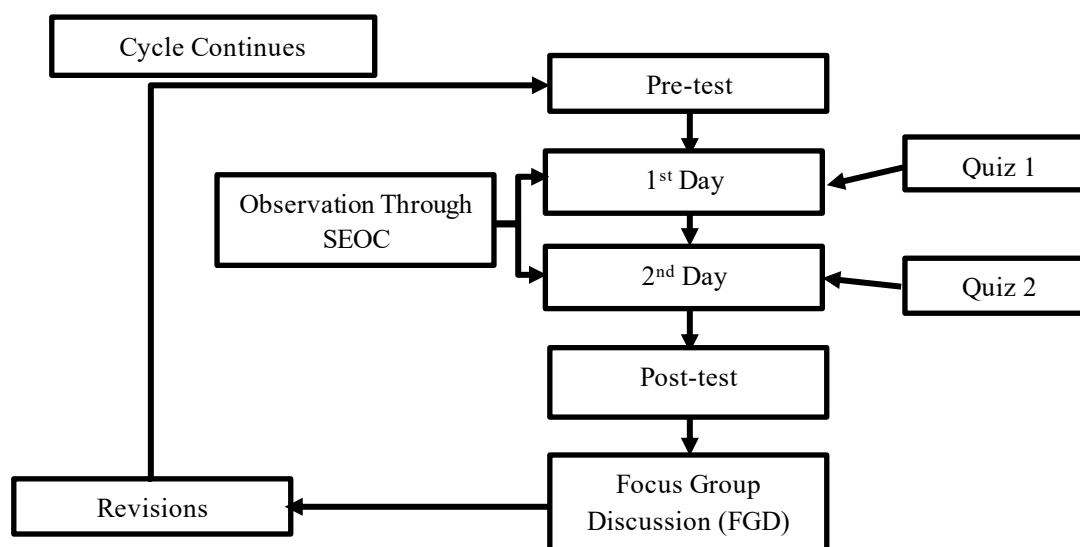


Figure 3: Flowchart of the Data Collection Process

The iterative process begins with a pre-test to establish baseline knowledge, followed by two days of instructional interventions with formative quizzes to monitor progress, and a post-test to measure overall learning. During implementation, four researchers observe student engagement using the SEOC tool. Afterward, participants provide qualitative feedback via a Focus Group Discussion (FGD). This qualitative feedback, combined with assessment and observation data, is analyzed to evaluate the intervention's effectiveness and guide revisions for a continuous cycle of improvement.

Ethical Standards

Ethical standards were strictly upheld following approval from the Visayas State University Health Ethics Review Committee (VSU HERC) under protocol number 2025-130-FTE. Informed parental consent and student assent were secured, emphasizing that voluntary participation could be withdrawn at any time without penalty. To ensure confidentiality under the Data Privacy Act of 2012 (RA 10173), data were anonymized using participant codes (e.g., P1) and stored securely for a five-

year retention period. The researchers declared no conflicts of interest and minimized bias by conducting sessions after class hours, maintaining clear researcher boundaries, and thoroughly familiarizing themselves with the SEOC checklist before data collection. Lastly, potential risks were mitigated by fostering a supportive, non-coercive environment that actively addressed student anxiety.

Limitations

While this study offers valuable insights into the VIMCC approach, several limitations apply. The small sample size from a single school limits the generalizability of the findings across other institutions, grade levels, or regions. Additionally, the short-term intervention may not reflect long-term retention. Data collection—relying on tests, quizzes, observation checklists, and feedback—might not capture all facets of conceptual understanding, and uncontrolled variables like prior knowledge, learning styles, and resource access could have influenced the results. Nevertheless, the study establishes a foundational baseline for future research.

Data Analysis

The data analysis in this research was categorized into three parts in accordance with the triangulation method (see **Table 3**), as outlined below:

- (1) Formative Assessments: Pre-tests, post-tests, and quizzes' scores were analyzed through mean percentage scores (MPS), bar graphs with error bars, paired t-test, and normalized gain by Hake (1998), $g = \frac{(posttest)-(pretest)}{100-(pretest)}$, to determine the effectiveness of the VIMCC Approach in promoting conceptual understanding and the students' improvement before, during, and after the implementation.
- (2) SEOC (Classroom Observation): SEOC results were examined using mean percentage scores (MPS) and bar graphs with error bars, guided by the adopted descriptive scale ranges (Lingling, 2023) to measure students' engagement and behavior, while also illustrating the variability and dispersion of data.
- (3) FGD (Focus Group Discussion): Students' perceptions and reflections after the implementation were recorded, transcribed, and analyzed using Braun & Clarke's (2006) 6-step thematic analysis: familiarization (transcribe/read), coding (inductive/deductive), theme generation/review, definition/naming, reporting linked to objectives.

Cycle comparisons were analyzed via graphs/tables to confirm VIMCC effectiveness.

Table 3: Data Collection and Analysis in each Research Question

Research Question:	Data Collection Method (Triangulation Approach)	Data Analysis
Q1: Performance	Pre-test and Post-test, Quizzes	Bar Graph with Error Bars, Mean Percentage Score (MPS), Normalized Gain, Paired t-test
Q2: Student Engagement	Observational tool SEOC	Mean Percentage Score (MPS), Bar Graph with Error Bars, Adopted Descriptive Scale Range (Lingling, 2023)
Q3: Students' perceptions	Focus Group Discussion	Braun & Clarke's (2006) 6-Step Thematic Analysis

RESULTS AND DISCUSSION

Following the triangulation method, this section will discuss the findings from formative assessments, classroom observations, and student responses in Cycle 1 in analyzing the effectiveness of the VIMCC approach, along with the adjustments made in the interventions that led to Cycle 2.

CYCLE 1 FINDINGS

Formative Assessment Results (Findings for Research Question 1)

Low pre-test scores in **Table 4** showed that students had limited understanding of subatomic particles, indicating the need for targeted instructional interventions. This might be because students find atomic concepts difficult due to their abstract nature and limited concrete representation in traditional teaching (Clamohoy et al., 2025). For instance, junior high school students in Philippine public schools demonstrated weak prior knowledge in chemistry concepts, particularly those involving atomic models, due to their limited visualization and conceptual scaffolding (Dela Cruz et al., 2025). In response to this challenge, the results showed a clear improvement in student performance (see **Table 4**). The mean score rose from 13.875 in the pre-test to 17.25 in the post-test, while the Mean Percentage Score (MPS) increased from 69.38% to 86.25%. This shift moves students from an "approaching proficiency" level to a "proficient" level of understanding, demonstrating that the instructional intervention effectively enhanced their mastery of the concepts.

The paired-samples t-test further confirmed that the improvement was statistically significant, $t(7) = -4.00, p = 0.005$. Because the p-value is less than 0.05, the null hypothesis is rejected, indicating the score increase is due to the intervention rather than chance. Furthermore, Cohen's d yielded an effect size of -1.41, representing a very large, meaningful impact on learning outcomes. This significant gain highlights the effectiveness of using interactive, visual-based instructional interventions to improve conceptual understanding in science, matching findings that tools like concept mapping, strategic intervention materials, and activity-based learning heavily enhance mastery of abstract concepts (Borabo & Dio, 2025).

Table 4: Paired t-test for Pre-test and Post-test Scores in Cycle 1

Test	Mean	Mean Percentage Score	t-statistic	df	p	Cohen's d	Normalized Gain
Pre-test	13.875	69.38	-4.00	7	0.005	-1.41	0.55
Post-test	17.25	86.25					

Additionally, the normalized gain score of 0.55 indicates a moderate improvement in students' conceptual understanding. This shows that learners achieved more than half of their potential learning gains, developing a deeper understanding of atomic structure. While the interventions proved effective, the results suggest that further instructional refinement is needed to address remaining misconceptions and fully deepen mastery.

Table 5: Quiz Mean Percentage Scores (MPS) Per Day in Cycle 1

	MPS (Mean Percentage Score)	Mean Difference
Day 1: Atomic Theory	82.5%	12.5%
Day 2: Atomic Models	95%	

Table 5 shows a 12.5% increase in mean scores from Day 1 to Day 2, indicating improved retention and a deeper understanding of atomic concepts as instruction progressed. This aligns with the spiral progression approach mandated by the Enhanced Basic Education Act of 2013 (Republic Act No. 10533), which emphasizes reinforcing prerequisite concepts before introducing more complex subjects. This growth demonstrates that students' science performance improves significantly when strategic intervention materials and formative assessments are used to consolidate foundational ideas (Borabo & Dio, 2025). Building this solid baseline is critical for understanding subatomic particles, as it provides the necessary context for how protons, neutrons, and electrons are structured and interact (Department of Education, 2020). Additionally, Filipino learners develop a stronger grasp of chemistry when instruction continually revisits key ideas using varied representations rather than treating topics as isolated lessons (Dela Cruz et al., 2025).

Participants' Engagement Through SEOC (Findings for Research Question 2)

The SEOC results for Cycle 1 described the students' behaviors during the two-day implementation. The mean scores in **Figure 4** show that Effort and Initiative were consistently high, while Disruptive and Inattentive behaviors remained low across both days.

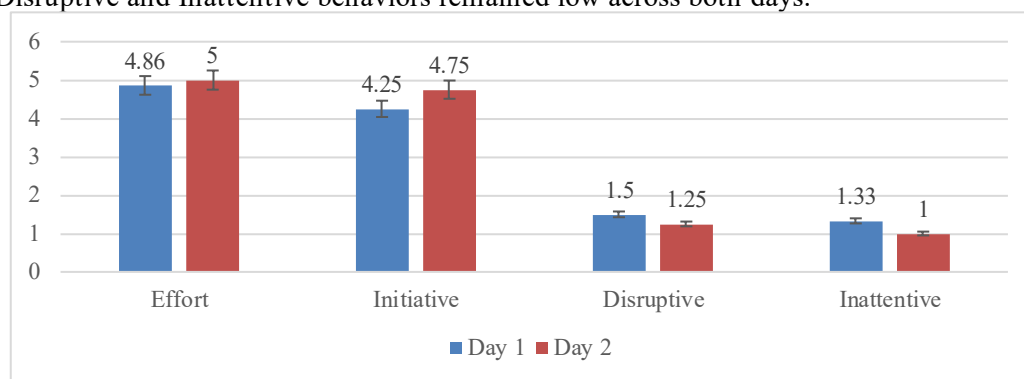


Figure 4: Mean Scores of SEOC Scale for Cycle 1

The high Effort and Initiative mean scores indicate that students were actively engaged and willing to participate in tasks, which strongly aligns with the improved learning outcomes. This engagement can be attributed to the interventions, which fostered active involvement. Interventions supporting student autonomy encourage learners to take initiative and become more proactive (Reeve et al., 2020). The findings further show that students demonstrated a high commitment to completing tasks, particularly those requiring less intensive manipulation (Al Mamun & Lawrie, 2023), and sustained effort typically enhances overall educational outcomes (Berhanu et al., 2025). These interactive activities likely strengthened effort and initiative, contributing to the reduction of disruptive and inattentive behaviors.

Conversely, the low mean scores for Disruptive and Inattentive behaviors suggest a supportive learning environment with fewer interruptions and better focus. Clear structure and guided activities naturally minimize these behaviors (Berhanu et al., 2025). Despite this, the non-zero mean scores reveal that some students still exhibited occasional off-task behaviors and relied on teacher guidance to begin, showing that independent engagement was inconsistent. This pattern often stems from fluctuations in engagement as task difficulty increases, which can temporarily reduce attention among certain learners (Heemskerk & Malmberg, 2020).

The increased effort and initiative demonstrated by the students suggest that the interactive, visual, and meaning-centered activities effectively enhanced their engagement in learning. By making the concepts more meaningful and easier to understand visually, these activities encouraged students to participate more actively in classroom tasks. As a result, disruptive and inattentive behaviors were minimized during classroom instruction.

Students' Insights About the Used Interventions (Findings for Research Question 3)

As part of the triangulation process, a focus group discussion was conducted to validate and explain the results obtained from formative assessments and classroom observations.

Theme 1: Positive Learning Experience

Many learners in Cycle 1 described the activities as fun, comfortable, and engaging, thereby creating a positive classroom atmosphere and encouraging active participation. One participant stated, "*It is fun actually, because there are a lot of activities which I really enjoyed*" (P1), while another shared, "*For me, it was fun and engaging activities that were made, and I love it*" (P2). These responses suggest that interactive tasks increased student involvement and that enjoyment in learning encouraged more active participation and confidence in expressing ideas. Active learning strategies increase student engagement and improve learners' attitudes toward science lessons compared to traditional lecture-based approaches (Yunzal et al., 2023).

Learners also noted that guidance made difficult tasks easier to understand and that support helped them overcome initial confusion. One participant explained, *“There are also questions which I thought were hard, but with the help, it was actually easy”* (P3). This response highlights the importance of scaffolding, where guided instruction helps students build understanding step by step and reduces frustration and cognitive overload. Structured guidance, combined with active learning, improves comprehension and helps students manage complex concepts more effectively (Yunzal et al., 2023).

Theme 2: Interest and Motivation to Learn More

Cycle 1 activities increased learners' interest and motivation to explore abstract scientific concepts. Many participants expressed curiosity about atomic structures and subatomic particles, noting that the activities helped them visualize concepts that cannot be directly observed. One learner shared, *“The interesting point of view of seeing something that can't be seen in our human eyes inspired me”* (P3), highlighting how visualization and interactive approaches stimulated interest. Exposure to unseen concepts made learning more intriguing and meaningful for students. Meaningful and interactive learning experiences promote curiosity and increase students' interest in science, as learners become more actively involved in understanding complex ideas rather than memorizing information (Rosete & Olua, 2024). This indicates that curiosity emerged naturally when students were encouraged to explore abstract content through engaging activities.

Despite experiencing confusion during the learning process, learners remained motivated to continue learning. One participant stated, *“Yes, I want to learn more about the atomic models because I'm confused”* (P4), suggesting that confusion did not discourage learning but instead encouraged deeper inquiry. This response reflects productive confusion, where uncertainty motivates students to seek understanding. Inquiry-based, student-centered approaches support this process by encouraging questions, exploration, and reflection. When students are actively involved in inquiry and problem-based tasks, their interest and engagement increase even when the content is challenging (Sarsale & Langub, 2023). The desire to learn more despite confusion shows that motivation was sustained throughout Cycle 1.

Theme 3: Improved Conceptual Understanding

Implemented interventions supported learners' improved understanding of atomic models and subatomic particles. Several participants shared that the use of 3D models helped them visualize abstract concepts that are usually difficult to imagine. One participant stated, *“The 3D model activity deepened our understanding of subatomic particles by clarifying differences between models”* (P4). Another learner added, *“I was finally able to determine the difference between the models”* (P5). These statements show that visual representations allowed learners to compare atomic models more clearly and meaningfully. Research supports the claim that concrete and visual learning materials help students form clearer mental images, which leads to a better understanding of abstract scientific ideas (Zheng et al., 2022). When learners can see and manipulate representations, they are more likely to connect ideas and recognize differences between scientific concepts.

In addition to 3D models, the timeline activity helped learners understand the sequence of atomic discoveries. One participant shared, *“The timeline activity made it easy to plot and identify the sequence of discoveries”* (P6). These structured activities helped learners logically organize information and grasp the historical development of science. Research confirms that multimedia and structured tools enhance conceptual understanding by helping students link concepts and events rather than memorizing isolated facts (Kaamiño & Hussien, 2024). By integrating visual models and chronological tools, the Cycle 1 interventions successfully helped learners bridge abstract ideas and scientific reasoning.

Theme 4: Learning Difficulties Encountered

Despite the positive learning experiences and increased interest observed during Cycle 1, several learning difficulties were encountered by the learners. Some participants reported difficulty identifying the states of matter, particularly when activities required them to classify pictures. One participant stated, *“The activity I probably struggled with was identifying the picture whether it was a gas, liquid, or solid”* (P7). This difficulty indicates that foundational concepts were not fully

mastered, highlighting a need for clearer explanations, more examples, and guided practice. When foundational concepts are not adequately reinforced before introducing higher-level tasks, learners often struggle to apply them effectively (Del Mundo & Caballes, 2022).

Learners also struggled to remember scientists' names and correctly match them with their atomic models. One participant shared, "*The only thing that is difficult is memorizing the names of scientists because there are so many*" (P8). This challenge reflects the high cognitive demand of remembering multiple unfamiliar names, models, and concepts, which can cause cognitive overload and hinder retention. High cognitive load often interferes with learning when students are still developing conceptual understanding and organizational strategies (Del Mundo & Caballes, 2022). This explains why learners struggled to remember factual details, like scientists' names, despite being actively engaged.

Another difficulty identified by participants was understanding unfamiliar scientific terms used in questions and instructions. One learner stated, "*There are some difficulties I had, like answering questions for which there are other words I didn't know*" (P1). Limited vocabulary hindered some learners' full understanding of the tasks despite their interest in the lesson. While inquiry-based and student-centered approaches increase curiosity and engagement, learners still struggle if scientific language and key terms are not explicitly taught or scaffolded (Sarsale & Langub, 2023). This highlights that interactive strategies must be paired with clear vocabulary instruction and structured guidance to reduce cognitive load and maximize learning.

Transitioning to Cycle 2 Based on Cycle 1 Findings

While the Cycle 1 findings show that the initial intervention effectively enhanced students' conceptual understanding of subatomic particles, the results also highlighted the need for further refinement to address remaining misconceptions. Guided by these insights, the researchers implemented revised interventions in Cycle 2 to target these gaps and strengthen overall conceptual mastery (see Table 6).

Table 6: Results-Intervention Matrix

Key Findings from Cycle 1	Specific changes/ Improvements Implemented for Cycle 2
Lower quiz scores during Day 1 compared to Day 2	Formative review and guided questioning were added before the Day 1 quiz to reinforce key concepts.
Difficulty identifying states of matter during concept mapping	Real-life physical examples were incorporated during the concept mapping activity to support concrete understanding.
Difficulty remembering scientists and atomic model timelines	Atomic theory timelines were presented as storytelling through an animated YouTube video.
Difficulty understanding and using scientific terms	The Frayer Model was modified to include guided definitions and visual representations.
Increased curiosity about subatomic particles but lingering confusion	Additional enrichment explanations were added during the Elaborate phase to deepen understanding.
Occasional low participation and classroom management concerns	Clear classroom rules and structured group roles were implemented to improve participation and behavior

CYCLE 2 FINDINGS

Following the implementation of the revised VIMCC Approach interventions, Cycle 2 quantitative and qualitative data showed marked improvements in student performance, engagement, and conceptual insights. The results revealed higher quiz and assessment scores alongside increased active participation and more positive student feedback. These findings suggest that the targeted modifications effectively bridged previous learning gaps, maintained student interest, and enhanced overall conceptual understanding.

Formative Assessment Results (Findings for Research Question 1)

As shown in **Table 7**, the Cycle 2 pre-test and post-test results indicate that the enhanced VIMCC interventions further improved students' understanding of subatomic particles. While Cycle 1 demonstrated effective conceptual change, Cycle 2 yielded higher initial and final scores overall. This improvement suggests strong retention of prior learning and confirms that the revised interventions successfully deepened students' conceptual understanding.

The statistical results demonstrate stronger effects in Cycle 2 where the *t*-value slightly increased in magnitude from -4.00 in Cycle 1 to -4.15 in Cycle 2, while the *p*-value decreased from 0.005 to 0.004, indicating a more statistically significant improvement. Moreover, the effect size (Cohen's *d*) increased from -1.41 to -1.47, both of which are interpreted as very large effects, but with Cycle 2 showing a stronger impact.

In addition, Cycle 2 yielded a high normalized gain of **0.79**, indicating that students achieved a significantly larger proportion of their maximum potential learning improvement than in Cycle 1. This substantial gain confirms that the score increases reflect conceptual mastery rather than chance. The consistent growth across mean scores, MPS, statistical significance, effect size, and normalized gain demonstrates that the refined interventions became steadily more effective over time.

Table 7: Cycle 1 and 2 Paired t-test for Pre-test-Post-test Comparison

Cycle	Test	Mean	Mean Percentage Score	t-statistic	df	<i>p</i>	Cohen's <i>d</i>	Normalized Gain Score
1	Pre-test	13.875	69.38	-4.00	7	0.005	-1.41	0.55
	Post-test	17.25	86.25					
2	Pre-test	15.125	75.63	-4.15	7	0.004	-1.47	0.79
	Post-test	19.00	95.00					

The significant improvement in students' test scores across both cycles underscores the VIMCC Approach's potential to effectively enhance conceptual understanding of atomic structure. Because chemistry is inherently abstract, visual representations offer spatial coherence and completeness that help learners process invisible structures more effectively (Bobek & Tversky, 2016). Furthermore, the interactive nature of game-based learning tasks has been shown to boost conceptual retention (Cruz, 2023), while meaning-centered graphic organizers like concept maps and the Frayer model effectively reveal existing knowledge and secure key vocabulary mastery (Ekinci & Şen, 2020; Labajo, 2024; Sacapaño & de Castro, 2022). Collectively, these studies empirically support the positive trends in **Table 7**, confirming the value of the active, visual, and game-based strategies integrated into the VIMCC Approach.

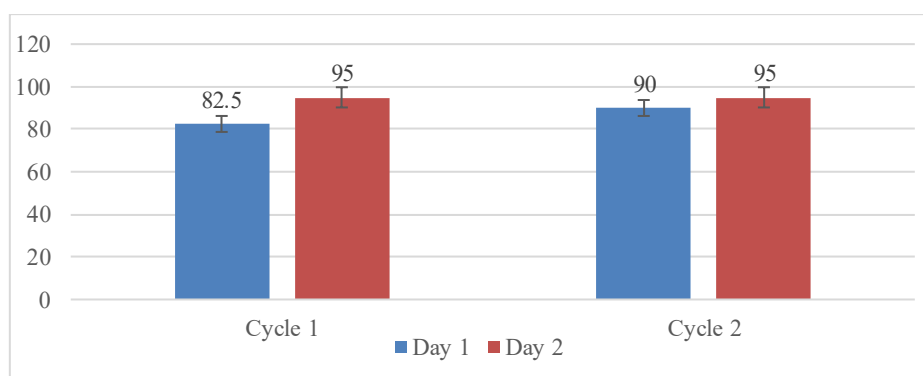


Figure 5: Quiz Mean Score Per Day Comparison of Cycle 1 and 2

In both cycles (see **Figure 5**), quiz scores increased from Day 1 to Day 2, with Cycle 2 maintaining a consistently higher performance baseline of 90%–95%. This sustained performance

indicates improved retention and understanding following the refined VIMCC interventions, culminating in high post-test scores. Overall, the steady progress across both cycles suggests that the daily layout was effective: Day 1 successfully introduced the core concepts, while Day 2 deepened mastery through highly guided and engaging activities.

Participants' Engagement Through SEOC (Findings for Research Question 2)

Cycle 2 SEOC results showed a highly positive shift: Effort and Initiative increased, while Disruptive and Inattentive behaviors dropped or remained low (see **Figure 6**). The increase in Effort and Initiative suggests that clearer conceptual support, explicit terminology scaffolding, and structured activities made students more willing to persist and start tasks independently. Meanwhile, well-defined group roles and clear expectations kept students focused, minimizing Disruptive and Inattentive behaviors. These behavioral improvements demonstrate that the refined VIMCC Approach effectively maintains an environment that fosters a strong understanding of atomic structure.

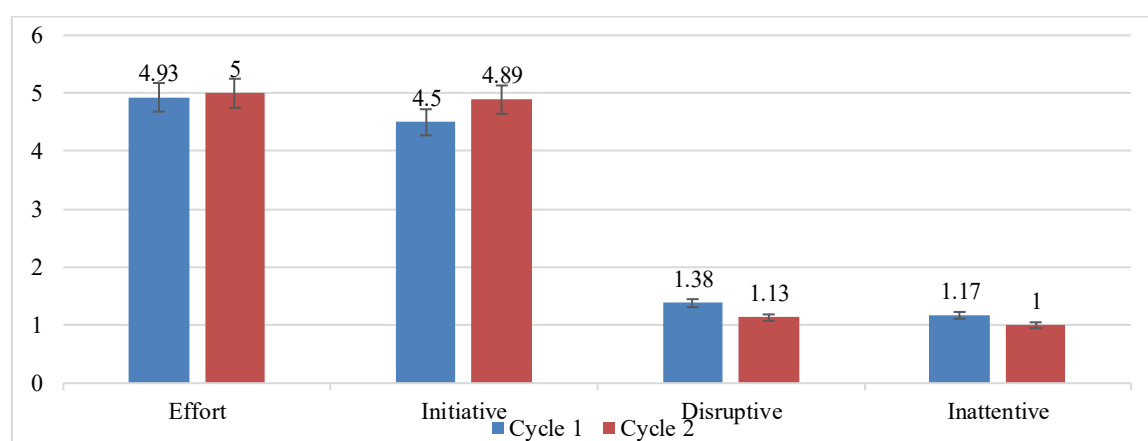


Figure 6: Mean SEOC Results Comparison of Cycle 1 and Cycle 2

This interpretation is consistent with active learning research showing that interactive and student-centered strategies improve student engagement, motivation, and academic outcomes (Alisoy, 2025; Yunzal et al., 2024; Munna & Kalam, 2021). It also aligns with constructivist theory, which emphasizes that learners become more engaged when they actively build knowledge through exploration, interaction, and participation (Zajda, 2021). In addition, Self-Determination Theory explains that when learning supports autonomy, competence, and relatedness, students are more likely to show persistence, attention, and motivation (Ryan & Deci, 2000). Supportive classroom conditions and guided learning may have helped reduce off-task behavior by keeping students focused and involved during instruction (Cebelleros & Buenaventura, 2024). Consequently, clear explanations, structured activities, and improved classroom management in Cycle 2 help learners remain focused during instruction, thereby reducing the likelihood of inattentive and disruptive behaviors.

Students' Insights About the Used Interventions (Findings for Research Question 3)

Theme 1: Increased Engagement and Motivation Toward Learning Atomic Structure

Students found the activities included through the VIMCC Approach as enjoyable and engaging, which encouraged participation and improved focus. One student shared, *"The activities were engaging and fun"* (P1). Another said, *"The activities helped me understand subatomic particles better and made the topic more interesting"* (P2). Several students reported that they participated to deepen their understanding, not merely because the activities were enjoyable (P3, P5). Engagement was driven by both the design of the activities and students' intrinsic motivation. Compared to Cycle 1, Cycle 2 showed increased participation and attention, building on the enjoyable and interactive experiences of the first cycle. Game-based and student-centered strategies increase engagement and

motivation in science learning. A systematic review found that educational games can increase learning motivation and fun, while fostering understanding of chemistry content (Byusa et al., 2022). This finding underscores the importance of optimizing the educational and motivational dimensions of learning activities when studying complex, abstract topics in Chemistry. Furthermore, combining enjoyable activities with curiosity-driven motivation can sustain engagement with complex topics such as atomic structure.

Theme 2: Preference for the Effective Instructional Strategies Used

Students emphasized that the visual and interactive aspects of the VIMCC approach—such as color-coded cards, concept maps, and games—helped them organize ideas, retain concepts, and think critically. One student mentioned, *“The game-based activity helped me think critically and understand the subatomic particles better”* (P4). Another said, *“Color-coded cards helped me understand and remember the differences between the particles”* (P6). Several students noted that these strategies were more effective than traditional teaching methods that rely primarily on slides or lectures (P5, P7). The findings build on Cycle 1, in which visual tools such as 3D models and timelines supported conceptual clarity. Cycle 2 extended these strategies through increased interactivity and gamification. The shift from guided visual tools in Cycle 1 to interactive methods in Cycle 2 shows how scaffolding improves comprehension and critical thinking in science learning.

Theme 3: Improved Conceptual Understanding and Accuracy

Students reported a clearer understanding of subatomic particles, including their roles and locations. One student said, *“At first, I was confused about where electrons are, but after the explanation, I learned that electrons are located in shells outside the nucleus”* (P1). Another shared, *“I now know not only the particles but also the scientists behind each discovery”* (P3). Repeated lessons and scaffolded activities helped students retain information better. They were also more accurate in identifying protons, neutrons, and electrons (P2, P5, P8).

While students in Cycle 1 struggled to memorize names and scientific terms, Cycle 2 demonstrated significant improvements in conceptual clarity and accuracy due to repeated exposure and interactive activities. Active, immersive approaches like gamification heavily enhance conceptual understanding and knowledge retention in science (Al-Muqbali et al., 2026; Tanilong, 2026). This progression underscores that the visual support, interactive learning, and reinforced instruction provided by the VIMCC Approach collectively strengthen learning outcomes, helping students confidently distinguish among protons, neutrons, and electrons.

CONCLUSION AND IMPLICATIONS

This action research demonstrated that improving students’ conceptual understanding of atomic structure enabled them to more effectively distinguish among subatomic particles. The VIMCC approach supported students in developing a clearer and more accurate understanding of how the atom is structured through visual, interactive, and meaning-centered strategies. As a result, students moved beyond memorization and correctly identified the symbols, masses, charges, and locations of protons, neutrons, and electrons. Learners became more confident, participated more actively in class, and showed improved performance in assessments. Misconceptions were reduced as students learned to explain ideas using appropriate scientific terminology and logical connections, thereby making the lessons more meaningful and enjoyable.

The findings suggest that teachers should focus on strengthening students’ basic understanding of atomic concepts before introducing more complex topics. Leveraging visual, interactive, and meaning-centered conceptualization strategies helps make abstract ideas in Chemistry easier to understand and meet learning needs, especially for struggling students. The study supports practical teaching approaches in which students are given opportunities to actively participate in learning and be exposed to effective modes of presenting scientific concepts, while they are facilitated in a learning-focused environment. Teachers are encouraged to reflect on their existing teaching practices and to promote methods that emphasize understanding over memorization to improve students’ engagement, confidence, and overall performance in science.

RECOMMENDATIONS

Based on the findings of this study, science teachers are encouraged to adopt the VIMCC approach and similar learner-centered strategies to improve student understanding of abstract concepts. School leaders should likewise provide professional development opportunities that strengthen teachers' competencies in designing theory-informed interventions, utilizing visual tools, and conducting classroom action research. Furthermore, future researchers are encouraged to replicate this study across different settings, grade levels, and science topics—using larger sample sizes and longer intervention periods—to validate the effectiveness and long-term impact of the VIMCC approach.

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USE OF ARTIFICIAL INTELLIGENCE TOOLS

Artificial Intelligence (AI) tools were used solely to assist with grammar checking, organization, reference formatting, and phrasing suggestions. All research data, findings, and interpretations were derived strictly from classroom observations, pre-tests, post-tests, and focus group discussions. AI was not used to generate data, fabricate results, or replace researcher judgment. The authors assume full responsibility for the accuracy and integrity of the content, having carefully reviewed all AI-assisted outputs to ensure compliance with ethical and copyright standards.

REFERENCES

- Al Mamun, M. A., & Lawrie, G. (2023). Student-content interactions: Exploring behavioural engagement with self-regulated inquiry-based online learning modules. *Smart Learning Environments*, 10(1). <https://doi.org/10.1186/s40561-022-00221-x>
- Al-Muqbali, A., Al-Nabhani, Z., & Shahat, M. A. (2026). Digital game-based learning in science education: Advancing motivation and deep understanding among middle school girls. *Journal of Technology and Science Education*, 16(2), 423–445. <https://doi.org/10.3926/jotse.3839>
- Alisoy, H. (2025). ESL teaching methods and approaches: Essential strategies for encouraging effective language acquisition. *Global Spectrum of Research and Humanities*, 1(1), 3–11. <https://doi.org/10.69760/gsrh.0101202401>
- Astuti, T. N., Sugiyarto, K. H., & Ikhsan, J. (2020). Effect of 3D visualization on students' critical thinking skills and scientific attitude in chemistry. *International Journal of Instruction*, 13(1), 151–164. <https://doi.org/10.29333/iji.2020.13110a>
- Azizoğlu, N., Pekdağ, B., Sarioğlu, A. B., & Kuzucu, G. (2022). An inquiry-based instruction on the main subatomic particles: Enhancing high-school students' achievement and motivation. *Science Education International*, 33(1), 75–85. <https://doi.org/10.33828/sei.v33.i1.8>
- Bagley, W. C. (1938). An essentialist's platform for the advancement of American education. *Educational Administration and Supervision*, 24, 241–256.
- Bartlett, F. C. (1932). *Remembering: A study in experimental and social psychology*. Cambridge University Press.
- Bautista, J. C. (2024). Conceptual learning and scientific reasoning of the STEM students as influenced by metacognitive strategies. *International Advanced Research Journal in*

- Science, Engineering and Technology*, 11(12), 18–24.
<https://doi.org/10.17148/iarjset.2024.111204>
- Berhanu, A., Semela, T., & Moges, B. (2025). Development and validation of a secondary school classroom engagement instrument in math and science in the Ethiopian context. *Frontiers in Psychology*, 16, 1491615. <https://doi.org/10.3389/fpsyg.2025.1491615>
- Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology*, 3(2), 77–101. <https://doi.org/10.1191/1478088706qp063oa>
- Bobek, E., & Tversky, B. (2016). Creating visual explanations improves learning. *Cognitive Research: Principles and Implication*, 1, Article 27.
<https://doi.org/10.1186/s41235-016-0031-6>
- Borabo, J., & Dio, R. V. (2025). Effectiveness of Strategic Intervention Material (SIM) in improving Filipino students' performance in science and mathematics: A meta-analysis. *Journal of Basic Education Research*, 6(2), 151–160.
<https://doi.org/10.37251/jber.v6i2.1420>
- Byusa, E., Kampire, E., & Mwesigye, A. R. (2022). Game-based learning approach on students' motivation and understanding of chemistry concepts: A systematic review of the literature. *Heliyon*, 8(5), Article e09541. <https://doi.org/10.1016/j.heliyon.2022.e09541>
- Cassar, A. G., & Jang, E. E. (2010). Investigating the effects of a game-based approach in teaching word recognition and spelling to students with reading disabilities and attention deficits. *Australian Journal of Learning Difficulties*, 15(2), 193–211.
<https://doi.org/10.1080/19404151003796516>
- Cebelleros, A. G., & Buenaventura, V. P. (2024). Learning environment and teacher communication behavior as determinants of student engagement. *American Journal of Education and Technology*, 3(4), 1–13. <https://doi.org/10.54536/ajet.v3i4.3543>
- Clamohoy, D. M., Nabua, E. B., Lao-Lao, M. R. R., & Luzica, S. A. (2025). Foundational chemistry learning gaps in atomic structure and the periodic table: Development and application of a diagnostic mastery assessment. *International Journal of Research and Innovation in Social Science*, 9(12), 3615–3624.
<https://doi.org/10.47772/ijriss.2025.91200278>
- Cruz, Z. (2023). Game-based activities as a teaching strategy in chemistry for Grade 9 students. *Psychology and Education: A Multidisciplinary Journal*, 11(4), 540–547.
<https://doi.org/10.5281/zenodo.8203010>
- Debesa, L. B. (2025). Causes and effects of poor health among learners at Anninipan Elementary School as basis for intervention. *Asian Journal of Education and Social Studies*, 51(6), 347–356. <https://doi.org/10.9734/ajess/2025/v51i61998>
- Dela Cruz, M. T., Baltazar, A. D., Jr., Chua, M. F., Estrella, M. C., & Basilio, E. R. (2025). JHS science teachers' perspectives, practices, and challenges in teaching the atomic structure. *Indonesian Journal of Education (INJOE)*, 4(1), 666–681.
<https://felifa.net/index.php/INJOE/article/view/227>
- Del Mundo, D. C., & Caballes, D. G. (2022). Measuring cognitive load level in a multimedia learning environment towards the development of I-SIM. *Sapienza: International Journal of Interdisciplinary Studies*, 3(1), 268–283. <https://doi.org/10.51798/sijis.v3i1.232>
- Department of Education. (2020). *Project EASE (Effective Alternative Secondary Education): Chemistry module 10: What's inside the atom*. Bureau of Secondary Education.
- Department of Education. (2023). *MATATAG curriculum*.
<https://www.deped.gov.ph/matatagcurriculum/>
- Ekinci, S. & Şen, A.I. (2020). Investigating Grade 12 students' cognitive structures about the atomic structure: A content analysis of student concept maps. *International Journal of Science Education*, 42(6), 977–996. <https://doi.org/10.1080/09500693.2020.1744045>
- Feekery, A. (2023). The 7 C's framework for participatory action research: Inducting novice participant-researchers. *Educational Action Research*, 32(3), 1–16.
<https://doi.org/10.1080/09650792.2023.2234417>

- Fitriza, Z., & Gazali, F. (2018). Diagnosing students' conception on atomic structure using open-ended questions. *Journal of Physics: Conference Series*, 1013, 012097. <https://doi.org/10.1088/1742-6596/1013/1/012097>
- Hake, R. R. (1998). Interactive-engagement versus traditional methods: A six-thousand-student survey of mechanics test data for introductory physics courses. *American Journal of Physics*, 66(1), 64–74. <https://doi.org/10.1119/1.18809>
- Heemskerk, C. H. H. M., & Malmberg, L.-E. (2020). Students' observed engagement in lessons, instructional activities, and learning experiences. *Frontline Learning Research*, 8(6), 38–58. <https://doi.org/10.14786/flr.v8i6.613>
- Iran-Nejad, A., & Winsler, A. (2000). Bartlett's schema theory and modern accounts of learning and remembering. *The Journal of Mind and Behavior*, 21(1–2), 5–35.
- Jusgado, J. M. S. (2024). Effects of the implementation of an interactive students' notebook (ISN) on students' conceptual understanding of atomic structure and motivation towards science. *Journal of Interdisciplinary Perspectives*, 2(3), 102–112. <https://doi.org/10.5281/zenodo.10680261>
- Kaamiño, K., & Hussien, O. (2024). Multimedia approach in teaching science grade 7. *Psychology and Education: A Multidisciplinary Journal*, 17(3), 190–199. <https://ejournals.ph/article.php?id=25500>
- Kaya, A. (2023). Addressing student misconceptions about atoms and examining instructor strategies for overcoming them. *Journal of Pedagogical Research*, 7(4), 251–262. <https://doi.org/10.33902/jpr.202323077>
- Kindon, S., Pain, R., & Kesby, M. (Eds.). (2007). Participatory action research approaches and methods. *Routledge*. <https://doi.org/10.4324/9780203933671>
- Koto, I. (2020). Teaching and learning science using YouTube videos and discovery learning in elementary school. *Mimbar Sekolah Dasar*, 7(1), 106–118. <https://doi.org/10.17509/mimbar-sd.v7i1.22504>
- Labajo, C. M., Jr. (2024). Modified Frayer model and semantic map: Its effectiveness in enhancing the performance in science of Grade 7 science students. *International Journal of Research and Innovation in Social Science*, 8(3s), 1310–1324. <https://doi.org/10.47772/ijriss.2024.803090s>
- Laohapornchaiphan, J., & Chenprakhon, P. (2024). A review of research on learning activities addressing the submicroscopic level in chemistry. *Journal of Chemical Education*, 101(11), 4552–4565. <https://doi.org/10.1021/acs.jchemed.4c00156>
- Lingling, G. S. (2023). Correlation of engagement and study skills of junior high school students in science modular instruction amidst pandemic of the public secondary schools in Calbayog districts. *GSC Advanced Research and Reviews*, 16(01), 082–110. <https://doi.org/10.30574/gscarr.2023.16.1.0304>
- Mayer, R. E. (2021). *Multimedia learning* (3rd ed.). Cambridge University Press. <https://doi.org/10.1017/9781108894333>
- Munna, A. S., & Kalam, M. A. (2021). Impact of active learning strategy on the student engagement. *GNOSI: An Interdisciplinary Journal of Human Theory and Praxis*, 4(2), 96–114. <https://eric.ed.gov/?id=ED614302>
- Narang, K. K., & Lata, P. (2024). The construction of concept maps: enhancing learning and knowledge representation. *ShodhKosh: Journal of Visual and Performing Arts*, 5(1). <https://doi.org/10.29121/shodhkosh.v5.i1.2024.1743>
- Organisation for Economic Co-operation and Development. (2023). *PISA 2022 results: Country note—Philippines*. <https://www.oecd.org/publication/pisa-2022-results/country-notes/philippines-a0882a2d/>
- Pacturan, D. B., Sabacajan, B. T., & Nahial, W. L. (2024). Integration of Gamification in Teaching and Students' Academic Performance: Basis for Action Plan. *International Journal of Multidisciplinary: Applied Business and Education Research*, 5(3), 1013–1023. <https://doi.org/10.11594/ijmaber.05.03.24>

- Paivio, A. (1986). *Mental representations: A dual coding approach*. Oxford University Press.
- Piaget, J. (1952). *The origins of intelligence in children*. International Universities Press.
- Reeve, J., Cheon, S. H., & Yu, T. H. (2020). An autonomy-supportive intervention to develop students' resilience by boosting agentic engagement. *International Journal of Behavioral Development*, 44(4), 325–338. <https://doi.org/10.1177/0165025420911103>
- Republic Act No. 10533. (2013, May 15). *Official Gazette of the Republic of the Philippines*. <https://www.officialgazette.gov.ph/2013/05/15/republic-act-no-10533/>
- Rosete, E. R. B., & Olua, E. F. (2024). Motivational factors and academic performance of junior high school students in Urdaneta City. *Psychology and Education: A Multidisciplinary Journal*, 17(9), 987–1000. <https://doi.org/10.5281/zenodo.10818951>
- Ryan, R. M., & Deci, E. L. (2000). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. *American Psychologist*, 55(1), 68–78. <https://doi.org/10.1037/0003-066X.55.1.68>
- Sacapaño, R.C. & de Castro, F.M. (2022). Frayer model: A strategy to improve the science vocabulary of Grade 9 students of Bagbag National High School. *South Florida Journal of Development*, 3(3), 3419–3437. <https://doi.org/10.46932/sfjdv3n3-031>
- Sarsale, J. S., & Langub, M. K. C. (2023). Effects of student-centered learning approaches towards interest in science. *Journal of Research, Policy & Practice of Teachers and Teacher Education*, 13(2), 73–85. <https://doi.org/10.37134/jrpptte.vol13.2.5.2023>
- Second Congressional Commission on Education. (2024). *Miseducation: The failed system of Philippine education, EDCOM II year one report*. <https://edcom2.gov.ph/media/2024/02/EDCOM-II-Year-One-Report-PDF-022924.pdf>
- Susilaningsih, E., & Aprilia, N. (2022). Dissemination of diagnostic three tier multiple choice test instruments for misconceptions analysis of macroscopic, sub-microscopic, and symbolic students in chemical learning. *AIP Conference Proceedings*, 2597, 040008. <https://doi.org/10.1063/5.0102568>
- Sweller, J., van Merriënboer, J. J. G., & Paas, F. G. W. C. (1998). Cognitive architecture and instructional design. *Educational Psychology Review*, 10(3), 251–296. <https://doi.org/10.1023/A:1022193728205>
- Tanilong, V. D., & Cheng, R. J. F. (2026). Students' concept retention on the use of gamification in biology. *Preprints*. <https://doi.org/10.20944/preprints202601.1058.v1>
- United Nations Economic Commission for Africa. (n.d.). *Chapter 8: Problem analysis*. https://repository.uneca.org/bitstream/handle/10855/49332/CHAPTER_EIGHT.pdf
- Vygotsky, L. S. (1978). *Mind in society: The development of higher psychological processes*. Harvard University Press.
- Yunzal, A.N., Jr., & Casinillo, L. F. (2023). Effect of Physics Education Technology (PhET) simulations: Evidence from STEM students' performance. *Journal of Educational Research and Evaluation*, 4(3), 221–226. <https://doi.org/10.23887/jere.v4i3.27450>
- Yunzal, A. N., Jr., Rallos, A. G., Nanud, M. N., Ondoy, M. L., Ares, J. M., & Picardal, M. (2024). Exploring active learning strategies in science among senior high school STEM learners and teachers. *Science Education International*, 35(4), 369–381. <https://doi.org/10.33828/sei.v35.i4>
- Zajda, J. (2021). Constructivist learning theory and creating effective learning environments. In *Third international handbook of globalisation, education and policy research* (pp. 35–50). Springer. https://doi.org/10.1007/978-3-030-71575-5_3
- Zheng, R., Corder, H., & Spears, J. (2022). The impact of annotation on concrete and abstract visual representations in science education: Testing the expertise reversal effect. *Research and Practice in Technology Enhanced Learning*, 17, Article 18. <https://doi.org/10.1186/s41039-022-00194-y>

Lived Experiences of Science Educators on AI Use: A Descriptive Phenomenological Study

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Abstract. This study explores the lived experiences of science educators using artificial intelligence (AI), focusing on how these experiences shape their thinking processes. As AI becomes increasingly integrated into education, the study seeks to understand educators' subjective, first-person experiences beyond measurable instructional outcomes. It specifically examines how educators describe their use of AI and how these experiences relate to cognitive processes in teaching. A descriptive phenomenological design guided by Giorgi's (2009) method was employed to capture rich experiential accounts. Seven science educators from Baybay City, Leyte, were selected through purposive sampling based on active AI use. Data were gathered through semi-structured interviews conducted both synchronously and asynchronously. Analysis followed Giorgi's systematic steps: bracketing, meaning unit identification, transformation, and synthesis to derive the essential structure of the phenomenon. Findings reveal AI as a multifaceted support system that enhances pedagogical practice, cognition, and professional growth. Five key constituents emerged: (1) *AI as a pedagogical and learning support tool*, (2) *cognitive transformation in AI use*, (3) *emotional and experiential engagement*, (4) *critical thinking and ethical awareness*, and (5) *reconstruction of teacher identity*. Educators reported improved efficiency in lesson preparation, enhanced organization, flexibility, and deeper analytical engagement. Emotional responses included increased confidence and support, alongside caution due to concerns about accuracy and overreliance. Participants also demonstrated active evaluation and adaptation of AI-generated outputs, reinforcing human decision-making in instruction. A notable shift in identity emerged, from content provider to facilitator and lifelong learner. AI functions not merely as a tool but as a transformative presence in science education. It reshapes instructional practices, cognitive engagement, and professional identity. While it enhances efficiency and supports higher-order thinking, its effective integration depends on educators' critical, ethical, and reflective use. The study highlights the need to balance AI integration with the preservation of human cognition and professional responsibility in education.

Keywords: Artificial intelligence in education; science educators; lived experiences; cognitive processes; phenomenology

INTRODUCTION

The rapid advancement of artificial intelligence (AI) has significantly transformed education, particularly science education. AI-powered technologies such as chatbots, intelligent tutoring systems, automated feedback platforms, virtual simulations, and generative AI are increasingly being integrated into teaching and learning (Batsaikhan & Correia, 2024). These technologies enhance access to information, support personalized instruction, and facilitate complex problem-solving, enabling educators to adopt more innovative approaches to instruction (Kalyani, 2024).

Consequently, science educators are gradually incorporating AI into their instructional practices to support scientific inquiry, analytical thinking, and student learning (Parviz, 2024).

In science education, AI has been associated with the development of higher-order thinking skills, including analysis, evaluation, and creation (Vieriu & Petrea, 2025). AI tools assist educators in exploring scientific concepts, generating instructional materials, organizing ideas, and addressing complex problems more efficiently (Moemeke, 2024). Despite these benefits, concerns have emerged regarding the excessive reliance on AI, which may reduce independent thinking, critical reflection, and deep cognitive engagement among users (Zhai et al., 2024). While existing studies have extensively examined the effectiveness and outcomes of AI in educational settings, there remains a need to understand how educators personally experience and interpret its integration into their professional practice.

This study is anchored in the United Nations Sustainable Development Goal 4 (SDG 4), which promotes inclusive and equitable quality education and lifelong learning opportunities for all. The integration of AI into science education reflects ongoing efforts to improve educational quality through innovative and accessible technologies (Schmidt et al., 2025). However, achieving these goals requires more than the adoption of technological tools; it also requires understanding how educators experience, interpret, and meaningfully integrate AI into their instructional practice. Examining these experiences provides valuable insights into how AI can effectively support high-quality and inclusive science education.

Baybay City, Leyte, provides an appropriate setting for this study because it is home to higher education institutions where science educators are increasingly integrating digital technologies into teaching and learning. As educators who regularly engage students in scientific inquiry, critical thinking, and problem-solving, science educators are well positioned to describe the opportunities and challenges associated with AI integration in science education. Exploring their lived experiences within this local context offers insights into how AI is adopted, interpreted, and applied in everyday instructional practice. Although situated within a specific locality, the findings may also contribute to a broader understanding of AI integration in similar educational settings across the Philippines and beyond (Motukeeva et al., 2025).

Despite the growing body of literature on AI in education, most existing studies employ quantitative methods to examine its relationship with academic performance, learning outcomes, or cognitive development. Although these studies provide valuable statistical evidence, they often overlook the subjective meanings, perceptions, and everyday experiences of educators using AI in their instructional practice. Consequently, qualitative research that explores the lived experiences of science educators within specific disciplinary contexts remains limited (Kamalov et al., 2023). Understanding these lived experiences is essential to developing a more comprehensive understanding of the role of AI in science education beyond measurable outcomes.

To address this gap, this study employs a descriptive phenomenological approach to explore the lived experiences of science educators in using AI. By examining how educators perceive, interpret, and assign meaning to AI in their instructional practice, the study seeks to provide a deeper understanding of its influence on teaching and cognitive processes. The findings are expected to contribute to the growing discourse on AI in science education by informing educational practice, institutional policies, professional development initiatives, and future research. Ultimately, the study aims to support the responsible and meaningful integration of AI in science education in ways that promote innovative, inclusive, and high-quality learning.

RESEARCH OBJECTIVES

Specifically, this research addresses the following question: How do Science Educators describe their lived experiences in using AI in teaching and learning?

- How do science educators describe their experiences of using AI in teaching and learning?
- How do these experiences relate to their thinking processes?
- What meanings do science educators ascribe to their AI use?

METHODOLOGY

Research Design

This study used a descriptive phenomenological design to examine the lived experiences of science educators using artificial intelligence (AI). Descriptive phenomenology is appropriate for exploring the meaning of lived experiences rather than measuring variables (Creswell & Poth, 2018). This approach emphasizes rich, first-person accounts, allowing participants to directly describe their lived experiences.

Following Giorgi's descriptive phenomenological method (Giorgi, 2009), data were gathered through in-depth interviews that elicited participants' narratives about their use of AI, especially their thinking processes during teaching and learning. The narratives were then systematically analyzed: first, read for a sense of the whole; then divided into meaning units; converted into psychological expressions; and synthesized into a structural description of the phenomenon (constituents). This approach enabled an in-depth understanding of how science educators perceive, interpret, and make sense of their cognitive engagement with AI tools. It highlights how AI shapes their thinking, decision-making, problem-solving, and learning strategies in the educational environment.

Participants

This study included seven science educators, chosen intentionally using clear inclusion criteria to ensure their relevance to the topic. Participants were required to be science teachers (elementary, junior, or senior high school) currently or previously teaching STEM-related subjects. They also needed to have experience using AI tools such as ChatGPT, AI lesson planners, quiz generators, and similar AI-assisted technologies in their instructional practices, and they had to be willing to participate in an interview.

From the preliminary survey, the researchers identified a total of thirty-two educators who initially expressed willingness to participate in the study. These potential participants underwent screening based on the established inclusion criteria to ensure their suitability and relevance to the research objectives. Following the screening process, only seven science educators met all the required criteria and completed participation in the study. The remaining twenty-five potential participants were excluded for several reasons. Fourteen science educators later became unavailable or declined participation due to busy and demanding schedules, workload responsibilities, and other personal or professional matters. Five participants were fresh graduates majoring in science but had not yet taught science subjects in public or private school settings. Two potential participants declined participation because they had not taught science for approximately six years, making their experiences less aligned with the current objective of the study. Additionally, four potential participants were only generally familiar with AI tools but reported limited and infrequent use of AI in instructional contexts due to limited technological exposure and computer usage.

The demographic characteristics of the seven qualified participants are presented in Table 1. The table summarizes the participants' profiles, including their teaching level, years of teaching experience, educational attainment, and AI tools used in instruction. The participants represented different educational levels and possessed varied teaching experiences, providing a diverse range of perspectives on the integration of AI in science education.

Table 1. Demographic Profile of Study Participants (Science Educator)

Participants	Age	Teaching Experience (Months)	Subject Area	Remarks
P1	24	6	Physics	Met the criteria
P2	29	38	Biology	Met the criteria
P3	25	8	Biology	Met the criteria
P4	25	4	Chemistry & Physics	Met the criteria
P5	28	18	Earth Science, General Chemistry, & Physics	Met the criteria
P6	24	10	General Science	Met the criteria
P7	26	9	General Science	Met the criteria

Consequently, the seven qualified science educators were purposively selected because they were considered capable of providing rich, relevant, and meaningful insights pertinent to the study. This sample size aligns with recommendations for descriptive phenomenological studies, which favor small yet information-rich participant groups for in-depth exploration of lived experiences. All participants had direct experience with AI integration in teaching and learning, thereby supporting the collection of rich qualitative data.

Research Tools

This study used a semi-structured interview guide with open-ended questions to elicit rich, in-depth descriptions of participants' lived experiences. The instrument's flexibility allowed the researchers to probe further and follow the natural flow of the conversation, enabling participants to articulate their perspectives on AI use in instructional practice, particularly in relation to their thinking processes. Consistent with Englander's (2012) phenomenological approach, the interviews emphasized detailed, first-person accounts rather than predetermined or restrictive lines of questioning, thereby preserving the authenticity and depth of the participants' narratives.

To ensure the accuracy and completeness of the data, all interviews were audio-recorded using a reliable software application and a dedicated recording device. This was supplemented by contemporaneous note-taking, capturing non-verbal cues, contextual details, and preliminary analytical insights that may not be fully reflected in the audio recordings. These combined tools facilitated rigorous, comprehensive data documentation, supporting the study's credibility and trustworthiness.

Data Collection

Data were collected through in-depth interviews to capture participants' lived experiences with AI use in instructional practice. Although face-to-face interviews were initially planned, the researchers prioritized participants' preferences and comfort by allowing flexibility in the mode of participation. Of the seven (7) participants, five (5) participated through synchronous virtual interviews conducted via online calls, one (1) participant responded through a chat-based interview, and one (1) participant completed the interview through Google Forms. This resulted in a combination of synchronous and asynchronous online interviewing.

The use of multiple data collection methods was primarily intended to maximize participant participation and accommodate differences in availability, internet connectivity, technological access, and communication preferences. Providing flexible interview options enabled the researchers to recruit information-rich participants who might otherwise have been unable or unwilling to participate in a single interview format while remaining consistent with the phenomenological goal of obtaining detailed descriptions of lived experiences.

Although interview modes varied, all data collection procedures maintained the essential characteristics of phenomenological interviewing by encouraging participants to provide detailed descriptions of their personal experiences, meanings, and reflections.

Synchronous online interviews were conducted in a quiet, distraction-free setting and typically lasted 35–45 minutes. These real-time interactions allowed for immediate probing and clarification of responses. For participants who were less comfortable with live virtual interaction, asynchronous methods such as Google Forms and chat-based responses were utilized, enabling them to provide thoughtful and reflective answers at their own pace while maintaining comfort and accessibility.

Consistent with qualitative online interviewing literature, asynchronous interviews may provide participants with additional time for reflection, while synchronous interviews allow immediate probing and clarification of meanings (Du & Zhang, 2022). Despite differences in interview mode, all participants were guided using the same semi-structured interview questions aligned with the phenomenological objectives of the study to maintain consistency and depth of narratives.

The researchers also recognized that the mode of data collection could potentially influence the richness and nature of participants' responses. Synchronous interviews generally yielded more spontaneous narratives and allowed follow-up questions for clarification, whereas asynchronous responses tended to be more deliberate and reflective but offered fewer opportunities for immediate

probing. To minimize these potential influences, the researchers used the same interview protocol across all modes, applied consistent follow-up questions whenever feasible, and analyzed all responses using the same phenomenological procedures. This approach ensured that variations in interview mode did not compromise the credibility, dependability, and overall trustworthiness of the findings.

Participants were assured that their chosen mode of participation would not affect the integrity of the study, provided that they offered rich and relevant descriptions of their experiences. To ensure comprehensive data capture, detailed field notes were taken during and immediately after each interview. These notes documented nonverbal cues (when applicable), contextual factors, and reflexive researcher observations, enriching the dataset and supporting a more nuanced analysis.

Data Analysis

This study used Giorgi's Descriptive Phenomenological Method (Giorgi, 2009). It systematically analyzed interview data to uncover the essential structure of participants' lived experiences regarding AI use in instructional practice.

Following Giorgi's five-step analytic process, the researcher first adopted the phenomenological attitude through bracketing (*epoché*), setting aside prior assumptions and biases to remain grounded in the participants' descriptions. Second, each transcript was read multiple times to obtain a holistic understanding of the narratives. Third, the data were delineated into meaning units at psychological significance points, allowing key aspects of the experience to emerge. Fourth, these meaning units were transformed into psychologically sensitive expressions, preserving participants' original intent while making implicit meanings explicit. Finally, the transformed meaning units were synthesized into a coherent and consistent structural description of the phenomenon.

Through this rigorous analytical procedure, the study generated a rich and nuanced understanding of how science educators experience and make sense of AI use, particularly in relation to their thinking processes, decision-making, and learning engagement.

To demonstrate the analytic rigor of the study, Table 2 provides an exemplar of how interview data were analyzed using Giorgi's descriptive phenomenological method. A raw participant quotation was first identified as a meaning unit. The meaning unit was subsequently transformed into psychological language to reveal its implicit experiential meaning. The transformed meaning then informed the development of a psychological constituent, which contributed to the essential structure describing science educators' lived experiences of AI use.

Table 2. *Exemplar of Giorgi's Analytic Transformation Process*

Raw Quotation	Meaning Unit	Transformed Meaning Unit	Constituent
"AI has made my thinking process faster but also more structured compared before." (P1)	AI improves the speed and organization of thinking.	The educator experiences AI as facilitating more efficient and systematically organized cognitive processing during instructional tasks.	Cognitive Transformation in the Use of AI

Trustworthiness and Rigor

To ensure the trustworthiness and rigor of the study, several qualitative validation strategies were employed throughout the research process. Consistent with Giorgi's descriptive phenomenological method, the researchers practiced *epoché* to minimize the influence of preconceived ideas and personal assumptions, allowing the phenomenon to be examined based on the participants' lived experiences. Reflexivity was continuously practiced by critically reflecting on the researchers' perspectives, decisions, and potential influences throughout the research process to maintain awareness of possible biases during data interpretation.

Peer debriefing was conducted through ongoing consultation with research mentors and qualitative research specialists who reviewed the emerging themes, meaning units, and interpretations to strengthen the credibility, consistency, and rigor of the analysis. Member checking

was likewise employed by returning the interpreted responses and emerging themes to the participants for confirmation, allowing them to verify whether the interpretations accurately represented their intended meanings and lived experiences. An audit trail was also maintained by systematically documenting the research procedures, data collection processes, coding decisions, theme development, and analytic reflections to enhance transparency and allow the research process to be traced and reviewed.

In addition, a consistent semi-structured interview guide was utilized across all interview modes to maintain alignment with the phenomenological objectives of the study and ensure consistency in data collection. The study also employed thick description through detailed participant narratives, transformed meaning units, and contextual interpretations to provide a rich and comprehensive understanding of the phenomenon. Verbatim quotations from participants were included to preserve the authenticity of their lived experiences and to support the credibility and validity of the findings.

Ethical Consideration

Informed consent was obtained from all participants, with the study's purpose, procedures, and potential risks and benefits clearly explained. Participant privacy was ensured through anonymization, which means removing identifying information from data, and strict confidentiality in accordance with the Philippine Data Privacy Act of 2012. The participants, who are science educators from different schools, were free to withdraw at any time. Ethical standards were upheld through fair participant selection and rigorous data collection and analysis, where 'rigorous' indicates careful, thorough procedures that ensure integrity and well-being.

RESULTS AND DISCUSSION

The lived experiences of science educators demonstrate that integrating artificial intelligence (AI) into teaching is transformational. AI not only supports efficiency in lesson planning and content delivery but also fundamentally reshapes pedagogical practice, cognitive processes, emotional engagement, and professional identity. With AI, educators manage complex teaching demands more effectively (Tan et al., 2024), and their thinking becomes faster and more flexible as they deepen analytical and problem-solving skills (Gerlich, 2025).

However, this experience is not purely functional but also emotional and reflective. Science educators initially feel eager and self-assured about AI, yet this is accompanied by caution and a growing sense of responsibility due to concerns about over-reliance on AI. As a result, they actively engage in critical evaluation, verifying and adapting AI-generated content to ensure its appropriateness for their students and alignment with educational standards. This reflective engagement reinforces their role as decision-makers, maintaining human judgment as central in the teaching process.

This section presents the emerging constituents derived from the participants' lived experiences as science educators using AI in teaching and learning. Data were collected through asynchronous and synchronous interviews. Researchers ensured that asynchronous questions aligned with research objectives to maintain consistency and depth.

The analysis yielded five key constituents: (1) *AI as a pedagogical and learning support tool*, (2) *cognitive transformation in the use of AI*, (3) *emotional and experiential engagement with AI*, (4) *critical thinking and ethical awareness in AI use*, and (5) *the reconstruction of teacher identity and meaning*. These findings are further discussed in relation to their implications for teaching and learning.

Together, these constituents distinctly illuminate how science educators perceive and make sense of AI integration, defining the core transformative structure of their experiences, as supported by relevant literature.

Constituent #1: AI as a Pedagogical and Learning Support Tool

Table 3 presents the findings on AI as a pedagogical and learning support tool. The findings reveal that science educators experience artificial intelligence (AI) as an essential pedagogical and learning

support tool that enhances both instructional practice and professional learning. Participants (educators) described using various AI applications for lesson preparation, content generation, assessment design, and laboratory activity development. Generative AI platforms such as ChatGPT, Co-pilot, Perplexity AI, Gemini, and Canva AI were commonly used to develop lesson explanations, instructional examples, and alternative ways of presenting scientific concepts, while AI-powered quiz generators and content creation tools streamlined routine instructional tasks.

One participant explained,

“ang paggamit nako og [my use of] AI has become part of my daily teaching routine, especially in lesson preparation and content development...” (P1),

Another participant shared,

“I use AI tools for generating lesson outlines, quizzes, and even laboratory activity guides.” (P3).

Table 3. *AI as a Pedagogical and Learning Support Tool*

Participant ID	Meaning Unit (MU)	Verbatim Statement (Translated to English)	Transformed Meaning (Giorgi Psychological Language)	Constituent (Essential Structure of Experience)
P1, P2, P5	AI is integrated into daily teaching tasks and workload management	<i>“Based on my experience, using AI has become part of my daily teaching routine, especially in lesson preparation and content development...”</i> <i>“As a teacher, there are so many tasks every day, so AI has helped me in making my work more efficient...”</i> <i>“For me, using AI is very helpful, especially in managing the workload...”</i>	The educator experiences AI as an embedded pedagogical support that enhances organization and delivery of instruction.	AI as a Pedagogical and Learning Support Tool
P1, P5, P7	AI is used to generate and organize lesson materials and assessments	<i>“Usually, I use AI tools for generating lesson outlines, quizzes, and even laboratory activity guides...”</i> <i>“It helps me organize ideas faster and gives me alternative ways to explain science concepts...”</i> <i>“I usually use AI for creating lesson plans, assessment tools, and simplifying difficult science concepts...”</i>	AI functions as a tool for generating and organizing instructional materials.	
P2, P3, P6, P7	AI is used to enhance understanding of science content for teaching	<i>“Sometimes, I also use it for my own understanding of complex topics before I discuss them with my students...”</i> <i>“It also helps me improve my understanding of topics that are not my strongest areas...”</i>	AI supports cognitive comprehension that informs teaching practice.	
P1, P4, P5, P6	AI is used for continuous professional learning and updating knowledge	<i>“I also use it for my own learning... so AI helps me explore different explanations quickly...”</i>	AI is experienced as a resource for continuous professional development.	

These experiences suggest that AI is no longer viewed merely as a supplementary technology but has become integrated into educators' everyday instructional practices. Rather than replacing teachers' expertise, participants described AI as extending their instructional capacity by reducing the time spent on routine preparation while allowing greater attention to lesson quality, concept

explanation, and classroom planning. The findings also indicate that educators intentionally select different AI tools depending on the instructional task, demonstrating that AI serves complementary rather than uniform functions in science teaching.

Beyond classroom preparation, participants also described AI as a valuable resource for their own professional learning. One educator stated,

“I also use it for my own learning... so I can better understand complex topics before I discuss them with my students.” (P2),

This finding highlights that educators experience AI not only as a teaching assistant but also as a learning companion that supports continuous professional development. By providing immediate access to updated scientific information, multiple explanations, and instructional resources, AI enables teachers to strengthen both their subject-matter knowledge and pedagogical readiness before classroom instruction.

These findings extend previous studies that describe AI primarily as a productivity tool by demonstrating its broader pedagogical value in science education. Rather than simply improving efficiency, participants perceived AI as supporting instructional flexibility, enriching lesson preparation, and fostering continuous learning. This reinforces previous work emphasizing AI's contribution to instructional planning and resource development (Fitria, 2023; Harrasi et al., 2025), while also supporting the view that AI promotes lifelong professional learning among educators by facilitating access to current knowledge and pedagogical support (Perez-Ortiz et al., 2021).

Constituent #2: Cognitive Transformation in the Use of AI

Table 4 highlights how AI influences the cognitive processes and decision-making practices of science educators. The findings indicate that AI meaningfully transforms how science educators think, analyze information, and make instructional decisions. Participants consistently described AI as enhancing cognitive efficiency by helping them organize ideas, process scientific information more quickly, and evaluate multiple instructional approaches. Rather than functioning as a replacement for teachers' thinking, AI was experienced as a cognitive support tool that strengthened analytical reasoning and instructional planning.

Participants also differentiated their experiences according to the type of AI tool they used. Generative AI platforms were commonly associated with higher-order thinking processes, including comparing explanations, examining alternative perspectives, and refining lesson content. In contrast, AI lesson planners and assessment generators primarily reduced the cognitive demands of routine planning, enabling educators to devote more attention to pedagogical reflection and classroom decision-making. These experiences suggest that different AI tools support distinct dimensions of teacher cognition, ranging from task efficiency to deeper conceptual analysis.

One participant explained,

“I can quickly get multiple perspectives from AI and compare ideas fit for the students...” (P2),

Similarly, another educator shared,

“I can compare different explanations and choose the best one for my students.” (P7).

Rather than accepting AI-generated information without question, participants described using multiple AI responses to compare ideas, evaluate their accuracy, and determine which explanations best matched students' learning needs. This indicates that AI supports reflective instructional decision-making by encouraging educators to critically examine information before applying it in the classroom. Consequently, the use of AI appears to reduce cognitive workload associated with information searching while simultaneously promoting evaluative thinking and pedagogical judgment.

These findings suggest that AI facilitates cognitive transformation by expanding educators' access to diverse perspectives without diminishing their professional autonomy. Instead of replacing human

reasoning, AI functions as a scaffold that supports deeper understanding, flexible thinking, and evidence-informed instructional choices. This interpretation complements previous research demonstrating that AI enhances cognitive engagement, analytical thinking, and instructional problem-solving (Alshammari & Alrehaili, 2025; Imran et al., 2024; Ruiz-Martín et al., 2024).

Table 4. *Cognitive Transformation in the Use of AI*

Participant ID	Meaning Unit (MU)	Verbatim Statement (Translated to English)	Transformed Meaning (Giorgi Psychological Language)	Constituent (Essential Structure of Experience)
P1, P6, P7	AI speeds up cognitive processing and understanding	<i>"AI has made my thinking process faster but also more structured compared before..."</i>; <i>"AI has improved my ability to understand and analyze science concepts faster..."</i>; <i>"AI has made my thinking process faster and more flexible in analyzing topics..."</i>	AI accelerates cognitive operations in learning and teaching tasks.	Cognitive Transformation in the Use of AI
P1, P4, P5	AI expands thinking through multiple perspectives	<i>"I can quickly get multiple perspectives from AI and compare ideas..."</i>; <i>"I am no longer limited to a single perspective because AI provides multiple explanations..."</i> <i>"It allows me to see different ways of explaining a concept..."</i>	AI broadens cognitive interpretation through varied viewpoints.	
P2, P5, P7	AI supports comparison and evaluation of ideas	<i>"It gives me different perspectives that I can compare before I decide what to teach..."</i>; <i>"It helps me analyze topics more deeply through different explanations..."</i> <i>"I can easily compare different explanations and choose the best one for my students..."</i>	AI promotes evaluative and comparative thinking processes.	
P1, P4, P6	AI makes thinking more structured and flexible	<i>"My thinking process is now more structured because I refine ideas from AI..."</i> <i>"AI has helped me become more flexible in analyzing problems..."</i>; <i>"I have become more structured and reflective before deciding on a teaching strategy..."</i>	AI reorganizes thinking into more systematic and adaptable processes.	

Constituent #3: Emotional and Experiential Engagement with AI

Table 5 presents the emotional and experiential responses of science educators toward AI integration in their teaching practices. The findings reveal that science educators' experiences with AI extend beyond cognitive and instructional benefits to include meaningful emotional and experiential dimensions. Participants described a progression in their emotional responses, beginning with curiosity and excitement as they explored AI and gradually developing confidence, reassurance, and professional responsibility through continued use. These experiences demonstrate that educators' engagement with AI is shaped not only by its technical capabilities but also by how it influences their confidence and teaching practice.

One participant shared,

"I feel relieved and supported when using AI in my teaching tasks because it helps me organize my lesson plans more easily and provides guidance in explaining complex topics." (P2)

Another participant added,

"It also helps save time, especially in preparing activities and assessments, which reduces the pressure in my teaching workload." (P4)

Table 5. Emotional and Experiential Engagement with AI

Participant ID	Meaning Unit (MU)	Verbatim Statement (Translated to English)	Transformed Meaning (Giorgi Psychological Language)	Constituent (Essential Structure of Experience)
P1, P4, P6	Initial excitement and positive adaptation to AI use	<i>"At first, I felt curious and excited because it was a new tool..."</i> <i>"At first, I was excited because it seemed like a new support system..."</i> <i>"I feel more confident and supported because AI makes my work easier..."</i>	AI evokes initial enthusiasm and adaptive engagement in teaching practice.	Emotional and Experiential Engagement with AI
P2, P5, P7	AI creates feelings of support and confidence	<i>"I feel relieved and supported when using AI in my teaching tasks..."</i> ; <i>"I feel more confident and supported when I use AI..."</i> ; <i>"I feel more efficient and supported because AI helps reduce my workload..."</i>	AI generates emotional assurance and professional confidence.	
P1, P2, P6	AI use involves caution due to accuracy concerns	<i>"However, there are also times when I feel hesitant due to concerns about accuracy..."</i> <i>"I remain cautious because I know it is not always 100% accurate..."</i> ; <i>"I remain cautious because not all information from AI is accurate..."</i>	AI use is accompanied by cautious emotional awareness of uncertainty.	
P4, P6, P7	AI use creates a sense of responsibility and accountability	<i>"I felt a sense of responsibility because I really need to check the outputs..."</i> ; <i>"It is helpful, but it still requires responsibility in using it..."</i> <i>"I still need to validate everything before using it in class..."</i>	AI use fosters accountability in verifying and applying outputs.	

These accounts suggest that AI contributes to educators' sense of professional support by reducing the demands of routine instructional tasks. Rather than simply improving efficiency, participants perceived AI as alleviating workload-related stress, allowing them to approach lesson preparation with greater confidence and focus. This emotional reassurance may encourage educators to devote more attention to instructional quality and student learning instead of administrative and planning burdens.

Despite these positive experiences, participants consistently emphasized that their trust in AI was accompanied by caution. Educators acknowledged that AI-generated responses may contain inaccuracies and therefore require careful evaluation before being used in the classroom. As one participant explained, they remain hesitant because AI is not always accurate and recognize the need to verify its outputs before integrating them into instruction.

This finding indicates that science educators do not perceive AI as an authoritative source of knowledge but rather as a supportive resource that complements, rather than replaces, professional judgment. Their willingness to validate AI-generated content reflects a strong sense of ethical and instructional responsibility, demonstrating that human expertise remains central to educational decision-making. The coexistence of confidence in AI's usefulness and caution regarding its limitations illustrates a balanced relationship in which educators benefit from technological support while maintaining accountability for the quality and accuracy of classroom instruction.

These findings extend existing research by showing that educators' emotional engagement with AI is characterized by both empowerment and critical awareness. While previous studies have highlighted AI's role in reducing workload and enhancing teacher confidence (Tang & Liao, 2025), the present findings further demonstrate that educators actively regulate their use of AI through continuous verification and professional judgment. This reinforces recommendations that human oversight remains essential in AI-assisted education to ensure the accuracy, reliability, and appropriateness of instructional materials (Cecilio-Fernandes & Sandars, 2025; Egunjobi, 2025; Lee & Song, 2024; Mondal & Mondal, 2024; Nazaretsky et al., 2022; Taheri et al., 2025).

Constituent #4: Critical Thinking and Ethical Awareness in AI Use

Table 6 presents the critical thinking processes and ethical considerations of science educators in using AI for instructional purposes. The findings reveal that science educators experience AI as a tool that strengthens rather than replaces their professional judgment. Participants consistently emphasized that AI-generated outputs require careful evaluation, modification, and contextualization before they can be integrated into classroom instruction. Rather than accepting AI-generated information at face value, educators described exercising critical thinking to ensure that instructional materials remain accurate, appropriate, and aligned with curriculum standards and students' learning needs.

One participant explained,

"I evaluate if the explanation is aligned with the curriculum level before I use it in my teaching and I make sure that the content is appropriate for my students' level of understanding, sometimes revising or simplifying the explanation so it will match their needs and learning capacity." (P4)

Similarly, another educator shared,

"I adjust answers to fit my students' level" (P5).

These accounts suggest that educators perceive AI-generated content as an initial resource rather than a finished instructional product. Their experiences demonstrate that the value of AI lies not in producing ready-to-use materials but in providing a foundation that teachers refine through their pedagogical expertise. By adapting AI outputs to curriculum requirements and learners' cognitive levels, educators preserve the contextual relevance and authenticity of classroom instruction while maintaining responsibility for instructional quality.

Participants also expressed awareness of the potential risks associated with excessive dependence on AI. Although they acknowledged its usefulness in supporting instructional tasks, they emphasized that over-reliance could weaken critical thinking and professional decision-making. Consequently, participants described using AI-generated responses as drafts or reference materials instead of final answers, reinforcing the importance of independent evaluation before classroom implementation.

This finding indicates that educators maintain a balanced relationship with AI by combining technological support with professional accountability. Rather than diminishing teachers' intellectual engagement, AI appears to encourage reflective practice by prompting educators to verify information, compare alternatives, and make informed instructional decisions. In this sense, critical thinking extends beyond verifying factual accuracy to include adapting content, exercising ethical judgment, and ensuring that AI-generated materials remain pedagogically appropriate.

These findings extend previous research by demonstrating that responsible AI integration depends not only on technological competence but also on educators' critical and ethical awareness. Consistent with constructivist perspectives, participants actively reconstructed AI-generated information to suit their instructional contexts instead of passively adopting it (Alam et al., 2026; Hasan, 2025; Wang et al., 2025; Zajda, 2021). This reinforces the view that AI serves as a catalyst for professional reflection while human expertise remains central to educational decision-making and instructional excellence (Tripathi et al., 2025).

Table 6. Critical Thinking and Ethical Awareness in AI Use

Participant ID	Meaning Unit (MU)	Verbatim Statement (Translated to English)	Transformed Meaning (Giorgi Psychological Language)	Constituent (Essential Structure of Experience)
P1, P2, P7	AI outputs must be verified before use	<i>"I still need to verify the information before using it in class..."</i>; <i>"I always double-check everything because AI is not always accurate..."</i>; <i>"I always validate information before using it in teaching..."</i>	Educators critically validate AI-generated outputs before application.	Critical Thinking and Ethical Awareness in AI Use
P4, P5, P6	AI outputs are adapted to curriculum and learner needs	<i>"I evaluate if the explanation is aligned with the curriculum level..."</i>; <i>"I adjust answers to fit my students' level..."</i>; <i>"I modify the content before using it in class..."</i>	AI outputs are contextualized based on educational requirements.	
P1, P6, P7	Awareness of over-reliance on AI is present	<i>"There's a risk of reduced critical thinking if someone relies too much on AI..."</i>; <i>"Sometimes it's very tempting to just rely on AI..."</i> <i>"I try to avoid over-reliance so I can still think independently..."</i>	Educators regulate dependence on AI to preserve cognitive autonomy.	
P1, P3, P5	Human judgment remains central in decision-making	<i>"I treat AI outputs as drafts or guides, not final answers..."</i>; <i>"I still make final decisions when using AI..."</i>; <i>"I still make final judgments based on my own analysis..."</i>	Educators maintain independent authority over instructional decisions.	

Constituent #5: Reconstruction of Teacher Identity and Meaning

Table 7 presents the changes in science educators' professional identity and the evolving meaning of their teaching roles in the context of AI integration. The integration of artificial intelligence (AI) reshapes how science educators understand their professional identity and purpose. Participants consistently described a transition from traditional teacher-centered roles toward more facilitative and learner-centered practices. Rather than viewing themselves primarily as providers of information, educators experienced their role as guiding students in constructing understanding, engaging with scientific concepts, and navigating AI-supported learning environments.

One participant reflected,

"It changed my role from being just a content provider to more of a facilitator and guide."
(P1)

Similarly, another educator shared,
“I have become more of a facilitator rather than just a source of knowledge.” (P5)

Table 7. Reconstruction of Teacher Identity and Meaning

Participant ID	Meaning Unit (MU)	Verbatim Statement	Transformed Meaning (Giorgi Psychological Language)	Constituent (Essential Structure of Experience)
P1, P4, P5	Teacher identity shifts from content provider to facilitator	<i>“It changed my role from being just a content provider to more of a facilitator and guide...”</i> ; <i>“From being just a lecturer to becoming more of a facilitator...”</i> ; <i>“I have become more of a facilitator and guide rather than just a source of knowledge...”</i>	Teachers reconstruct their identity as facilitators of student learning.	Reconstruction of Teacher Identity and Meaning
P2, P3, P6	Teachers redefine themselves as learning facilitators	<i>“It changed my role into someone who facilitates learning...”</i> ; <i>“It made me more of a facilitator of learning...”</i> ; <i>“I guide students more in understanding concepts critically...”</i>	Educators guide students toward critical and meaningful learning.	
P1, P6, P7	AI becomes part of professional growth and adaptation	<i>“It represents a shift... being a lifelong learner adapting to new technologies...”</i> ; <i>“It means continuous improvement as a professional educator...”</i> ; <i>“It means embracing innovation and continuous improvement...”</i>	AI encourages continuous learning and professional adaptability.	
P1, P5, P7	AI is understood as a tool for enhancement, not replacement	<i>“AI is a powerful tool but should not replace human thinking...”</i> ; <i>“AI is a tool for enhancement, not replacement...”</i>	AI enhances teaching without replacing human judgment.	

These experiences suggest that AI does not diminish the importance of teachers but instead redefines how their expertise is enacted in the classroom. As routine tasks such as content generation and lesson preparation become more technology-assisted, educators described shifting their attention toward facilitating learning, promoting inquiry, and supporting students' critical engagement with information. This transformation reflects a movement from knowledge transmission to learning facilitation, where teachers exercise pedagogical judgment to help students interpret, evaluate, and apply knowledge rather than simply receive it.

Participants also described this transition as requiring continuous professional growth. The rapid evolution of AI technologies encouraged educators to view themselves as lifelong learners who must continually adapt their knowledge and teaching practices. One participant explained that AI represents *“a shift towards being a lifelong learner adapting to new technologies”* (P1), while another emphasized the importance of *“continuous improvement as an educator”* (P6). These accounts indicate that professional identity is experienced as dynamic rather than fixed, evolving through ongoing learning, reflection, and adaptation to emerging educational technologies.

Despite embracing AI, participants consistently emphasized that human judgment remains indispensable in teaching. One educator summarized this perspective by stating,

“AI is a tool for enhancement, not replacement.” (P5)

This finding illustrates that educators perceive AI as complementing rather than substituting their professional expertise. While AI supports instructional planning and resource development, participants regarded ethical judgment, contextual decision-making, and meaningful student engagement as uniquely human responsibilities that cannot be delegated to technology. Consequently, AI integration was experienced not as a loss of professional identity but as an opportunity to strengthen teachers' roles as reflective practitioners, mentors, and facilitators of learning.

These findings extend contemporary perspectives on teacher identity by demonstrating that technological change influences not only instructional practices but also educators' understanding of their professional purpose. Consistent with previous research, teacher identity emerges as a dynamic construct that is continually reconstructed through experience, interaction, and engagement with evolving technologies (Graus et al., 2022; Pishghadam et al., 2022). However, the present findings further suggest that AI encourages educators to redefine professionalism by balancing technological competence with pedagogical expertise, ethical responsibility, and lifelong learning (Guilherme, 2017; Zhou & Peng, 2025).

A comparison of participants' teaching experience suggests subtle differences in how AI was experienced. Novice science educators (4–10 months of teaching experience) tended to emphasize AI as a source of instructional support, efficiency, and confidence-building, particularly in lesson preparation, content generation, and understanding unfamiliar concepts. Their narratives frequently reflected reliance on AI as a scaffold for navigating the demands of early teaching practice. In contrast, the more experienced educator (38 months of experience) described AI less as a source of immediate support and more as a tool for evaluating multiple perspectives, refining instructional decisions, and enhancing professional judgment. While both groups perceived AI positively, novice teachers appeared to focus on practical assistance, whereas the more experienced teacher highlighted analytical thinking and pedagogical decision-making. These findings suggest that teaching experience may shape how educators engage cognitively with AI, although further research involving a larger sample is needed to explore this relationship more fully.

The findings show that using artificial intelligence (AI) in teaching is more than just using a tool in which it affects how science educators teach, think, and make decisions. AI helps make tasks easier, gives different ideas, and supports deeper understanding, but teachers still carefully check, adjust, and improve the information before using it. This shows that while AI is helpful, teachers remain important in guiding learning. In the end, effective use of AI depends not on relying on it completely, but on using it thoughtfully to improve teaching and support better thinking in science education.

CONCLUSION AND IMPLICATIONS

This study explores how science educators describe using artificial intelligence (AI) in teaching and learning, revealing AI as an embedded pedagogical, cognitive, and professional support system. Science educators consistently described AI as a tool that enhances efficiency in lesson preparation, content generation, and continuous learning, while also shaping their emotional engagement through increased confidence, motivation, and cautious awareness. Beyond functional use, these experiences reflect a deeper transformation in how educators interact with knowledge, technology, and their instructional responsibilities, highlighting AI as a meaningful presence within their teaching practice rather than a peripheral tool.

More importantly, the findings clearly demonstrate that these experiences are directly linked to educators' thinking processes. The use of AI in generating multiple perspectives, organizing information, and verifying outputs promotes more structured, flexible, and analytical forms of thinking. Science educators also engage in higher-order cognitive processes such as evaluation,

comparison, decision-making, and metacognitive regulation as they interpret and adapt AI-generated content for instructional use. At the same time, the need to critically assess accuracy and avoid over-reliance reinforces reflective thinking and cognitive autonomy. This establishes that AI does not replace human cognition but actively reshapes it, functioning as a cognitive partner that enhances, extends, and refines educators' thinking processes within the teaching and learning environment.

These findings indicate that integrating AI in science education can both enrich cognition and transform pedagogy. Science educators must combine technical proficiency with critical thinking and ethical judgment to apply AI responsibly. Institutions should design professional development that addresses both the practical and conceptual aspects of AI, with special attention to the development of evaluative and reflective thinking. The results also support theories of constructivist and active learning, emphasizing that knowledge is built through interaction and engagement. Overall, AI integration underscores educators' evolving role as reflective practitioners who facilitate meaningful and rigorous learning through technology.

RECOMMENDATION & LIMITATION

Based on the findings of this study, it is recommended that future research further examine the relationship between AI use and cognitive processes by employing mixed-method or longitudinal designs to capture both experiential and measurable changes over time. Expanding the participant base across different subject areas and educational contexts would also provide a more comprehensive understanding of AI integration in education.

In practice, educational institutions are encouraged to implement structured training programs that go beyond basic AI tool utilization and focus on developing educators' critical evaluation skills, ethical awareness, and pedagogical decision-making. Additionally, clear institutional guidelines should be established to regulate AI use, ensuring that it supports learning while maintaining the central role of human judgment, professional responsibility, and cognitive independence in the teaching and learning process.

This study has several limitations that should be considered when interpreting its findings. First, the study involved only seven science educators from Baybay City, which is appropriate for descriptive phenomenological research that prioritizes depth of understanding over broad representation. However, the relatively small sample size, single-site setting, and focus on one disciplinary cluster limit the range of perspectives captured. Consequently, the findings may not reflect the experiences of educators from other geographic locations, institutional contexts, or academic disciplines where the integration of artificial intelligence (AI) may differ.

Second, although the study employed strategies such as bracketing (*epoché*), reflexive journaling, member checking, peer debriefing, and maintaining an audit trail to enhance trustworthiness, researcher interpretation remains inherent in qualitative data analysis. While these measures helped minimize potential bias, complete elimination of researcher subjectivity is not possible, and the interpretation of participants' lived experiences may have been influenced by the researcher's perspectives.

Finally, the study utilized both synchronous and asynchronous semi-structured interviews. While this approach increased participant accessibility and flexibility, asynchronous interviews may have limited opportunities for immediate probing and clarification, potentially affecting the depth and spontaneity of some responses. Although a common interview guide was used to ensure consistency across both interview modes, the findings should be viewed as context-specific rather than broadly generalizable. Instead, readers are encouraged to assess the transferability of the findings by considering the similarities between the study context and their own settings.

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USE OF ARTIFICIAL INTELLIGENCE TOOLS

Artificial intelligence (AI) tools were used to translate responses from Cebuano to English and to assist with grammar and spelling. These tools were applied solely for linguistic and editorial purposes, while all data interpretation and analysis were conducted by the researchers.

REFERENCES

- Alam, M. N., Islam, M. A., Babiker, M. O. A., Siddiqui, M. S., Amin, M. B., & Oláh, J. (2026). AI-assisted learning tools and student learning outcomes: A cognitive load theory perspective. *Computers in Human Behavior Reports*, 21, Article 100986. <https://doi.org/10.1016/j.chbr.2026.100986>
- Alshammari, S. H., & Alrehaili, T. A. (2025). The effect of teaching, social, and cognitive presence on student engagement in online courses: a structural equation modelling approach. *Acta Psychologica*, 258, 105183. <https://doi.org/10.1016/j.actpsy.2025.105183>
- Batsaikhan, B. (Zack), & Correia, A.-P. (2024). The effects of Generative Artificial Intelligence on Intelligent Tutoring Systems in higher education: A systematic review. *Studies in Technology Enhanced Learning*, 4(1). <https://doi.org/10.21428/8c225f6e.33570bb1>
- Cecilio-Fernandes, D., & Sandars, J. (2025). The hallucination of learning with generative artificial intelligence. *Medical Teacher*, 47(12), 2057–2058. <https://doi.org/10.1080/0142159x.2025.2531812>
- Du, Y., & Zhang, F. (2022). Examinees' affective preference for online speaking assessment: Synchronous VS asynchronous. *Chinese Language Teaching Methodology and Technology*, 5(1), Article 3. <https://engagedscholarship.csuohio.edu/cltm/vol5/iss1/3>
- Egunjobi, J. P. (2025). The misuse of AI-Generated content in academic and religious settings. *International Journal of Research and Scientific Innovation*, XII(XV), 871–879. <https://doi.org/10.51244/ijrsi.2025.121500077p>
- Fitria, T. N. (2023). The use of artificial intelligence in education (AIED): Can AI replace the teacher's role? *Epigram*, 20(2), 165–187. <https://doi.org/10.32722/epi.v20i2.5711>
- Gerlich, M. (2025). AI Tools in Society: Impacts on cognitive offloading and the future of critical thinking. *Societies*, 15(1), 6. <https://doi.org/10.3390/soc15010006>
- Giorgi, A. (2009). *The descriptive phenomenological method in psychology: A modified Husserlian approach*. Pittsburgh, PA: Duquesne University Press.
- Graus, M., Van De Broek, A., Hennissen, P., & Schils, T. (2022). Disentangling aspects of teacher identity learning from reflective blogs: The development of a category system. *Teaching and Teacher Education*, 111, 103624. <https://doi.org/10.1016/j.tate.2021.103624>
- Guilherme, A. (2017). AI and education: the importance of teacher and student relations. *AI & Society*, 34(1), 47–54. <https://doi.org/10.1007/s00146-017-0693-8>
- Harrasi, N. A., Subhi, N. A., Harthy, S. A., & Habsi, J. A. (2025). Learner perspectives on AI teacher effectiveness: The role of engagement, motivation, efficiency, and educational experience. *Social Sciences & Humanities Open*, 12, 101950. <https://doi.org/10.1016/j.ssaho.2025.101950>
- Hasan, M. K. (2025). How AI quietly undermines the joy and effort of learning: a call for rebalancing education in the digital age. *Annals of Medicine and Surgery*, 87(8), 4693–4694. <https://doi.org/10.1097/ms9.0000000000003456>
- Imran, M. a. U., Aziz, M. B., Tiwari, A., Saha, S., & Ghimire, A. (2024). Exploring the latest trends in AI Technologies: A study on current state, application and individual impacts. *Journal of Computer and Communications*, 12(08), 21–36. <https://doi.org/10.4236/jcc.2024.128002>
- Kalyani, L. K. (2024). The role of Technology in Education: Enhancing learning outcomes and 21st century skills. *International Journal of Scientific Research in Modern Science and Technology*, 3(4), 05–10. <https://doi.org/10.59828/ijrmst.v3i4.199>

- Kamalov, F., Calonge, D. S., & Gurrib, I. (2023). New era of Artificial intelligence in Education: Towards a sustainable Multifaceted Revolution. *Sustainability*, 15(16), 12451. <https://doi.org/10.3390/su151612451>
- Lee, S., & Song, K. (2024). Teachers' and students' perceptions of AI-generated concept explanations: Implications for integrating generative AI in computer science education. *Computers and Education: Artificial Intelligence*, 7, 100283. <https://doi.org/10.1016/j.caeai.2024.100283>
- Moemeke, C. (2024). Artificial Intelligence and Machine Learning in enhancing Science Learning Experiences: Exploring Possibilities and Concerns. *NIU Journal of Educational Research*, 10(2), 59-72. doi: 10.58709/niujed.v10i2.2000
- Mondal, H., & Mondal, S. (2024). Artificial Intelligence-Generated content needs a human oversight. *Indian Journal of Dermatology*, 69(3), 284. https://doi.org/10.4103/ijd.ijd_163_24
- Motukeeva, A., Azhibayeva, A., Kazieva, G., Zainiev, R., & Tokonbekova, K. (2025). Analysis of the features shaping students' thinking to enhance the educational process. *Higher Education for the Future*, 13(1), 25–49. <https://doi.org/10.1177/23476311251372249>
- Nazaretsky, T., Ariely, M., Cukurova, M., & Alexandron, G. (2022). Teachers' trust in AI -powered educational technology and a professional development program to improve it. *British Journal of Educational Technology*, 53(4), 914–931. <https://doi.org/10.1111/bjet.13232>
- Parviz, M. (2024). AI in education: Comparative perspectives from STEM and Non-STEM instructors. *Computers and Education Open*, 6, 100190. <https://doi.org/10.1016/j.caeo.2024.100190>
- Pérez-Ortiz, M., Novak, E., Bulathwela, S., & Shawe-Taylor, J. (2021). An AI-based learning companion promoting lifelong learning opportunities for all (arXiv Preprint No. arXiv:2112.01242). arXiv. <https://doi.org/10.48550/arXiv.2112.01242>
- Pishghadam, R., Golzar, J., & Miri, M. A. (2022). A new conceptual framework for teacher identity development. *Frontiers in Psychology*, 13, 876395. <https://doi.org/10.3389/fpsyg.2022.876395>
- Ruiz-Martín, H., Blanco, F., & Ferrero, M. (2024). Which learning techniques supported by cognitive research do students use at secondary school? Prevalence and associations with students' beliefs and achievement. *Cognitive Research: Principles and Implications*, 9(1), 44. <https://doi.org/10.1186/s41235-024-00567-5>
- Schmidt, D. A., Alboloushi, B., Thomas, A., & Magalhaes, R. (2025). Integrating artificial intelligence in higher education: perceptions, challenges, and strategies for academic innovation. *Computers and Education Open*, 9, 100274. <https://doi.org/10.1016/j.caeo.2025.100274>
- Taheri, R., Nazemi, N., Pennington, S. E., Clark, J. A., & Dadgostari, F. (2025). Factors influencing educators' AI adoption: A grounded meta-analysis review. *Computers and Education Artificial Intelligence*, 9, 100464. <https://doi.org/10.1016/j.caeai.2025.100464>
- Tan, X., Cheng, G., & Ling, M. H. (2024). Artificial intelligence in teaching and teacher professional development: A systematic review. *Computers and Education: Artificial Intelligence*, 8, 100355. <https://doi.org/10.1016/j.caeai.2024.100355>
- Tang, Z., & Liao, J. (2025). Unlocking emotional resilience: Exploring the impact of AI-enhanced support systems on EFL teachers' burnout and EFL students' well-being in modern classrooms. *Acta Psychologica*, 260, 105672. <https://doi.org/10.1016/j.actpsy.2025.105672>
- Tripathi, T., Sharma, S. R., Singh, V., Bhargava, P., & Raj, C. (2025). Teaching and learning with AI: a qualitative study on K-12 teachers' use and engagement with artificial intelligence. *Frontiers in Education*, 10. <https://doi.org/10.3389/educ.2025.1651217>
- Vieriu, A. M., & Petrea, G. (2025). The impact of artificial intelligence (AI) on students' academic development. *Education Sciences*, 15(3), 343. <https://doi.org/10.3390/educsci15030343>
- Wang, D., Dong, X., & Zhong, J. (2025). Enhance College AI Course Learning Experience with Constructivism-Based Blog Assignments. *Education Sciences*, 15(2), 217. <https://doi.org/10.3390/educsci15020217>
- Zajda, J. (2021). Constructivist learning theory and creating effective learning environments. In J. Zajda (Ed.), *Globalisation and education reforms* (pp. 35–50). Springer. https://doi.org/10.1007/978-3-030-71575-5_3
- Zhai, C., Wibowo, S., & Li, L. D. (2024). The effects of over-reliance on AI dialogue systems on students' cognitive abilities: a systematic review. *Smart Learning Environments*, 11(1). <https://doi.org/10.1186/s40561-024-00316-7>
- Zhou, M., & Peng, S. (2025). The usage of AI in teaching and students' creativity: the mediating role of learning engagement and the moderating role of AI literacy. *Behavioral Sciences*, 15(5), 587. <https://doi.org/10.3390/bs15050587>

Developing Computational Thinking in Primary School Students Through a Smart Farming Context Using the Engineering Design Process

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Abstract. The purpose of this research was to: (1) develop learning activities using the Engineering Design Process (EDP) within a smart farming context to enhance the computational thinking (CT) skills of primary school students, and (2) compare the students' CT skills before and after participating in these activities. The participants were 39 fifth-grade students from a large inclusive primary school in Thailand, selected through purposive sampling. The research employed a pre-experimental design. Research instruments included four EDP-based smart farming lesson plans totaling 12 hours of instruction, a CT concept test, and a performance-based CT rubric. The results indicated that the integration of the six-step EDP, ranging from identifying authentic agricultural problems to iteratively debugging automated sensor prototypes, significantly improved students' CT skills. Quantitative analysis revealed a statistically significant increase in overall CT skill scores, with the post-test mean ($M = 19.46$, $SD = 2.35$) being significantly higher than the pre-test mean ($M = 11.64$, $SD = 2.98$) at $p < .001$. Significant improvements were observed across all specific computational components, with the largest improvement occurring in conditional logic. Furthermore, qualitative data from the performance-based rubric and final smart farming projects confirmed that students effectively applied the four pillars of CT: decomposition, pattern recognition, abstraction, and algorithm design to solve real-world agricultural challenges. This study concludes that anchoring computational tasks in authentic, tangible contexts like smart farming successfully bridges the gap between abstract coding and meaningful physical outcomes.

Keywords: Computational thinking; Engineering Design Process; smart farming; primary education

INTRODUCTION

Computational thinking (CT) is a cognitive process that involves formulating problems and their solutions in a way that can be effectively executed by an information-processing agent (Wing, 2006; Barr & Stephenson, 2011). Quality education plays a pivotal role in equipping learners with CT skills, fostering the creativity necessary to comprehend and transform the world (Wing, 2006). By developing systematic approaches, CT enables learners to achieve efficient outcomes and apply these methods to diverse, everyday challenges (Grover & Pea, 2013). Consequently, CT is widely recognized not merely as a skill for computer scientists, but as a foundational competency for all individuals (Wing, 2006). The core principles of CT, such as decomposition, pattern recognition, algorithmic design, and abstraction, can be utilized to comprehend human behaviors and complex systems (Weintrop et al., 2016). In this study, a clear conceptual distinction is maintained between the two terms: “computational thinking” (CT) refers to the overarching cognitive process and

theoretical framework, whereas “computational thinking skills” refers to the measurable practical competencies—namely, decomposition, pattern recognition, abstraction, and algorithm design—that students develop and apply to solve problems. Furthermore, these principles are highly valuable for navigating unstructured problems in daily life (Yadav et al., 2016). In recent years, the promotion of CT in pre-university education has progressed significantly. Globally, primary and secondary education systems have increasingly emphasized the development of coding, logical reasoning, and problem-solving skills through educational robotics and digital applications (García-Peñalvo & Mendes, 2018; Hsu et al., 2018). Early childhood and primary education are considered optimal periods for introducing CT concepts (Montiel & Gomez-Zermeño, 2021). Consequently, various instructional approaches have been explored, ranging from the use of tangible smart toys (Lin et al., 2020) and simple robotics (Isnaini et al., 2019) to structured curricula introducing basic computer science concepts (Su & Yang, 2023) and novel assessment tools (El-Hamamsy et al., 2022). Despite this growing interest, the literature on the effective implementation of CT specifically in primary schools remains limited, necessitating further research into pedagogical methods that assist teachers in introducing CT concepts effectively (Chalmers, 2018). Recent systematic reviews further emphasize the need for engaging, context-driven CT activities for young learners (Paraskevopoulou-Kollia et al., 2025).

One compelling pedagogical approach to address this gap is the Engineering Design Process (EDP). EDP is a systematic problem-solving framework that operates under resource constraints to yield optimal outcomes (Mentzer et al., 2015). To establish a robust theoretical foundation for this approach, Moore et al. (2014) emphasize in their framework for quality K–12 engineering education that engineering design is a central mechanism for meaningful STEM integration. This framework highlights the critical role of engaging students in authentic problem solving, navigating design constraints, optimizing solutions, and utilizing iterative processes to address real-world applications. Integrating EDP into learning activities encourages students to engage in hands-on, step-by-step problem solving based on real-world situations, thereby fostering creativity and innovation (Kareemee, 2017). This process strongly aligns with constructivist learning theories and the Framework for K–12 Science Education, which emphasizes the integration of science, technology, and engineering practices (National Research Council, 2012; Phutwatthana, 2018). Moreover, integrating CT with EDP creates a robust conceptual framework that significantly enhances students’ problem-solving capabilities (Sonay & Kiray, 2022). Recent studies confirm that STEM-based EDP models effectively improve learning outcomes and critical thinking in elementary settings (Sutisnawati et al., 2025).

Despite these pedagogical advancements, several gaps remain in the current literature. First, there is a knowledge gap regarding how primary students transfer abstract, screen-based coding skills to tangible physical solutions. Second, a methodological gap exists in CT assessment; while prior studies often rely on standardized multiple-choice tests, there is a distinct lack of authentic, performance-based assessments that measure how students apply CT to solve multidimensional problems.

To address these gaps, this study introduces a contextual innovation by integrating the EDP-CT framework specifically within a smart farming environment. Smart farming is utilized not merely as a generic real-world backdrop, but because its inherent technological characteristics perfectly mirror core computational operations. Specifically, smart farming involves sensor-based data collection, conditional logic, automation, and environmental monitoring. These specific features directly align with the four pillars of CT: identifying complex crop issues requires *decomposition*, analyzing environmental trends utilizes *pattern recognition*, filtering non-essential environmental variables demands *abstraction*, and designing automated irrigation or lighting feedback systems necessitates precise *algorithm design*. Therefore, smart farming provides an unparalleled and highly specific setting that makes the abstract concepts of coding visible and impactful, successfully bridging the gap between theoretical computational models and meaningful physical outcomes.

RESEARCH OBJECTIVES

The specific objectives of this research are as follows:

1. To develop learning activities incorporating the Engineering Design Process (EDP) within a smart farming context to enhance the computational thinking skills of primary school students.
2. To compare the computational thinking skills of primary school students before and after their participation in the developed learning activities.

METHODOLOGY

This study employed a pre-experimental research design, specifically a one-group pre-test–post-test design, to measure changes in students’ computational thinking (CT) skills. Additionally, to capture the dynamic learning atmosphere and provide a deeper understanding of the students’ problem-solving processes and learning behaviors, qualitative data were gathered concurrently. Throughout the intervention, this information was collected via unstructured individual and group interviews, as well as classroom observations.

Participants

The target population comprised all fifth-grade students at a large inclusive primary school, totaling 207 students distributed across 5 classrooms. From this sampling frame, one classroom was selected using purposive sampling. Therefore, the participants consisted of 39 fifth-grade students (aged 10–11 years) enrolled in a science and technology course during the second semester of the 2022 academic year.

Research Instruments

The research instruments utilized in this study comprised instructional and data-collection tools:

EDP-Based Smart Farming Lesson Plans

A set of four Engineering Design Process (EDP)-based smart farming lesson plans, totaling 12 hours of instruction (one hour per week for 12 weeks), was developed for this study. The instructional design was anchored in the six-step EDP framework outlined by the National Research Council (2012): (1) identifying the problem, (2) gathering related information and concepts, (3) designing a solution, (4) planning and executing the solution, (5) testing, evaluating, and improving, and (6) presenting the outcomes. Prior to implementation, these lesson plans were validated by three subject-matter experts to evaluate content validity, alignment with learning objectives, and the appropriateness of the instructional activities. The evaluation results demonstrated an item-objective congruence (IOC) values ranging from .67 to 1.00 for all components, indicating high content validity.

To contextualize the learning experience, the instructor integrated an agricultural context through simulated scenarios across all four lesson plans. This approach provided students with specific, real-world conditions to guide their algorithm design and coding. The progression of the lessons began with “Night-Blooming Purslane,” where students explored the effects of light and temperature. Utilizing teacher-provided data on the light requirements of various plant species, students wrote code to control an artificial lighting system designed to trick a morning-blooming plant into flowering at night. The second lesson, “Little Garden to Care For,” focused on soil moisture. Students analyzed datasets detailing optimal moisture levels for different vegetables, allowing them to define variables and set conditional statements (if/else) to process sensor inputs for an automated watering system. In the third lesson, “Desired pH Levels,” students examined water quality data and developed code to trigger alerts when pH levels deviated from standard criteria necessary for healthy plant growth. Finally, the “Smart Farming” lesson culminated in large-scale farm management by integrating all previously explored parameters: light, moisture, and water quality. In this final stage, students designed a comprehensive, fully integrated sensor system aimed at reducing operational costs and increasing agricultural yields.

Crucially, this pedagogical design ensured that coding was not taught in an abstract or isolated manner. Instead, the teacher acted as a facilitator by supplying an “agricultural database” comprising specific environmental parameters required by the students’ chosen plants to serve as practical input data. Consequently, students were challenged to apply computational thinking skills to decompose these agricultural problems and translate numerical values into logical conditions within their programs. This intentional integration made the process of learning to code highly meaningful, directly demonstrating its applicability in solving authentic, real-world challenges.

Computational Thinking Skills Assessment

To comprehensively evaluate CT skills, two assessment formats were employed:

2.1 CT Concept Test. Adapted from the Computational Thinking Test (CT-test) developed by Román-González et al. (2017), this 28-item multiple-choice instrument comprehensively measures foundational computational concepts. The test addresses seven concepts and conditions: basic directions, loops (repeat times), loops (repeat until), simple conditionals (if), complex conditionals (if/else), while conditionals, and simple functions. Three subject-matter experts validated the adapted instrument, which achieved item-objective congruence (IOC) values ranging from .67 to 1.00 and a Cronbach’s alpha reliability coefficient of .76.

2.2 Performance-Based CT Rubric. The researcher developed a performance-based computational thinking (CT) assessment based on the “Four Pillars of Computational Thinking” framework and informed by Wing (2006) and Barr and Stephenson (2011). The assessment examines students’ proficiency in designing a logical, step-by-step method or flowchart to solve the prioritized problem effectively. To evaluate students’ practical problem-solving capabilities systematically within the prescribed agricultural context, a four-level scoring rubric was established in accordance with performance-assessment guidelines. The rubric yielded high IOC values (.67–1.00) and an excellent reliability coefficient of .96, as demonstrated in the example below.

Scenario: *In a small condo in the heart of the city, a young woman named “May” is deeply passionate about nature. She dreams of having a beautiful garden like in the movies. However, due to her hectic work schedule, she spends most of her time tied to a computer screen, making it difficult to care for plants. One day, May decided to buy small plants to decorate her room. She chose easy-to-care-for varieties recommended by the shop. Unfortunately, it wasn’t long before the leaves began turning yellow and falling off one by one. May felt very disappointed. She tried searching the internet for care instructions but still could not solve the problem. Q1: Based on the given scenario, break down the problem into clear sub-problems in a bulleted list. (Decomposition: 3 points) Q2: Group the identified sub-problems to show which ones are identical, similar, or fall into the same pattern. (Pattern Recognition: 3 points) Q3: Identify which sub-problems are essential and which are non-essential. Determine the most critical problem that should be considered first, and provide supporting reasons. (Abstraction: 3 points) Q4: Design a step-by-step flowchart to solve the problem based on the scenario. (Algorithm Design: 3 points)*

To clarify the evaluation process, each of the four questions (representing the four CT pillars) was scored on a four-level scale ranging from 0 to 3 points. The performance levels were defined as follows: 0 points (Needs Improvement), 1 point (Fair), 2 points (Moderate), and 3 points (Good). A summary of the scoring criteria is presented in Table 1. Consequently, the mean scores presented in Figure 2 represent the average points (out of a maximum of 3.00) achieved by the 39 students for each specific CT pillar across the learning activities. The qualitative performance levels reported in the results section directly correspond to the established score ranges: 0.00–0.49 (Needs Improvement), 0.50–1.49 (Fair), 1.50–2.49 (Moderate), and 2.50–3.00 (Good).

Data Collection

The intervention commenced with a pre-test using the CT skills assessments. Following the pre-test, the students participated in the 12-hour EDP-based smart farming learning activities over a 12-week period. Throughout the intervention, qualitative data were collected via unstructured individual

and group interviews, as well as observations. Upon completion of all lesson plans, a post-test was administered using the identical CT skills assessments.

Table 1: Summary of the scoring criteria for the performance-based CT rubric

CT Pillar	Level 0: Needs Improvement (0 pts)	Level 1: Fair (1 pt)	Level 2: Moderate (2 pts)	Level 3: Good (3 pts)
Decomposition	Cannot identify any relevant sub-problems from the scenario.	Identifies only one or two minor sub-problems; lacks clarity.	Identifies most sub-problems correctly but misses some key details.	Breaks down the problem into a clear, comprehensive, and accurate bulleted list.
Pattern Recognition	Cannot group sub-problems or identify any patterns.	Attempts to group problems but connections are illogical.	Groups most problems correctly based on similarities or patterns.	Accurately categorizes all identified sub-problems into highly logical patterns.
Abstraction	Cannot distinguish between essential and non-essential problems.	Identifies a critical problem but fails to provide a supporting reason.	Identifies the most critical problem with basic, somewhat vague reasoning.	Accurately prioritizes the most critical problem and provides strong, logical reasons.
Algorithm Design	Fails to provide a step-by-step solution or flowchart.	Designs a basic workflow but lacks clear sequence or standard symbols.	Designs a functional flowchart with minor sequence or symbolic errors.	Designs a highly logical, step-by-step flowchart using correct standard symbols.

Data Analysis

Quantitative data obtained from the pre-test and post-test were analyzed using descriptive statistics, including means and standard deviations. To determine whether CT skills differed significantly before and after the intervention, a paired-samples t-test was conducted. To ensure the reliability and consistency of the performance-based assessment, the students' assignments and final smart farming projects were evaluated by two independent raters. Prior to the formal evaluation, the raters participated in a calibration session using a small sample of student work to establish a shared understanding of the four-level rubric criteria. Interrater reliability was determined using the intraclass correlation coefficient (ICC). The resulting ICC of .87 indicated excellent interrater reliability. Any minor discrepancies in scoring were resolved through discussion to reach a final consensus. The qualitative data derived from interviews and task observations were analyzed using content analysis to support and triangulate the quantitative findings.

RESULTS AND DISCUSSION

Development of EDP-Based Smart Farming Learning Activities

The first objective of this study was to develop learning activities using the Engineering Design Process (EDP) within a smart farming context to enhance the computational thinking skills of primary school students. The instructional design engaged students in a hands-on, problem-solving environment. The learning progression and student activities across the six EDP stages are detailed as follows:

Step 1: Identifying the Problem (Decomposition). Students were presented with an authentic smart farming scenario, such as the story of a young farmer named “Ton” whose vegetables were wilting due to improper soil moisture. Observation notes revealed that students initially struggled to look

past the superficial details of the story. During an unstructured interview, one student remarked, “At first, our group thought the problem was just that Ton was lazy and didn’t have time to water the plants. But when we broke the problem down together, we realized the main issue was actually ‘improper soil moisture.’ So, we had to find a way to measure the moisture for him.” However, after teacher scaffolding, students successfully shifted to computational decomposition. Students analyzed the narrative to identify the core problems (e.g., wilting and stunted growth) and their root causes (e.g., incorrect watering and inadequate soil moisture). By breaking down the scenario, students practiced problem decomposition and proposed initial technological solutions, such as building a simple soil moisture meter. *Although most students successfully identified the relevant issues, a few struggled to align their identified causes with the specific scenario, highlighting the need for guided decomposition.*

Step 2: Gathering Information and Concepts (Pattern Recognition). Students studied supplementary materials and completed activity sheets to discover concepts relevant to the identified problem. Observation data indicated that students could effectively link gathered data and identify underlying trends (patterns) to design scalable solutions. Demonstrating this, one student noted, “I looked at the data in the table, and all these vegetables need similar moisture levels. If we use a soil moisture sensor, we can probably write the same pattern of code to control the watering for all the vegetable beds.” Through group discussions, each group shared data and brainstormed at least two potential solutions. The groups then evaluated and selected the optimal design, such as an automated watering system utilizing soil moisture sensors and an LCD data display.

Step 3: Designing a Solution (Abstraction and Algorithm Design). In this collaborative stage, students independently drafted preliminary models for their chosen solutions and selected the necessary materials and equipment. Interview feedback highlighted students’ abilities to filter out irrelevant information (abstraction), as one student explained, “When drawing the flowchart, we don’t need to care about the color of Ton’s plant pots or what kind of watering can he use; that’s not important. The most important part is the if/else condition: if the moisture is below 60, turn on the water pump; if not, turn it off.” They presented their initial sketches to the instructor, receiving constructive feedback to ensure their models practically addressed the scenario’s constraints. Students then dedicated time outside class to refine these models under the teacher’s facilitation.

Step 4: Planning and Executing. Students formulated a concrete workflow to execute their designs, continuously consulting with the teacher and reporting their progress. Observations of group dynamics highlighted strong collaborative execution, with students dividing tasks based on their algorithmic plans: “I’ll be in charge of wiring the sensor to the board and the water pump. You take the flowchart our group drew and put the command blocks together in the computer. That way, we can follow the plan and finish on time.” They translated their initial sketches into detailed blueprints and proceeded to construct the physical prototypes (e.g., the automated sensor system) exactly as designed.

Step 5: Testing, Evaluating, and Improving (Debugging). Students tested their constructed prototypes to determine whether they met the specified conditions and successfully solved the initial agricultural problem. If a prototype failed to operate as intended, students engaged in an iterative debugging process. They analyzed the malfunction, consulted with the instructor regarding material selection or design flaws, and refined the hardware or code until the system functioned perfectly. Teacher observations noted that during the debugging phase, students demonstrated high levels of engagement. When an irrigation pump malfunctioned, a group was observed systematically checking their code line-by-line rather than giving up, directly applying algorithmic thinking as they troubleshooted: “Hey! Why won’t the water pump stop? The water is overflowing the pot... Wait, don’t unplug the wires yet. Let me look at the code on the screen first. Oh! We forgot to add a ‘delay’ command and forgot to loop the sensor check. Let’s go through and fix the code line by line.”

Step 6: Presenting the Outcomes. In the final stage, students conducted live demonstrations to explain the functionality of their prototypes. During these presentations, students successfully articulated the connection between their code and the physical outcomes. One group synthesized their learning by explaining, “Our group’s ‘Smart Watering System’ was built to solve the problem of wilting

vegetables. We used step-by-step thinking to command the sensor to measure the moisture level before deciding to water. This system will save time and can actually do the work for humans.” They comprehensively presented their design concepts, detailing how their computational models and physical inventions effectively resolved the initial smart farming problem.

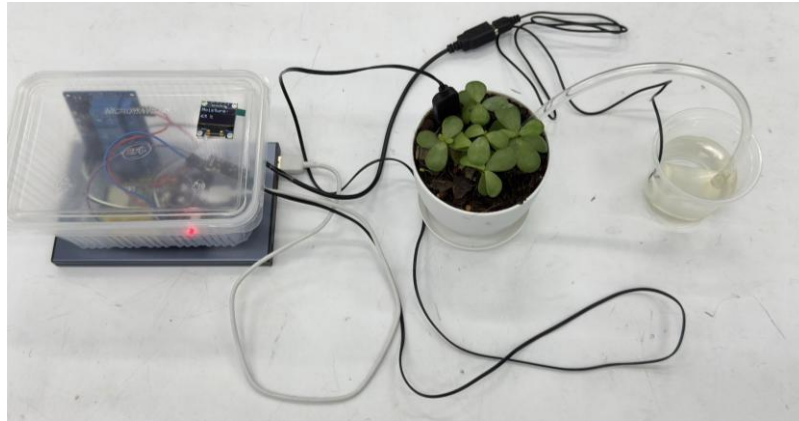


Figure 1: Implementation of the automated irrigation prototype in a simulated smart farming environment.

Comparison of Computational Thinking Skills

To address the second research objective, a paired-samples t-test was conducted to compare students’ computational thinking skills—specifically, their understanding of core computational concepts—before and after participating in the EDP-based smart farming learning activities. The statistical comparison of these pre-test and post-test scores across seven computational concepts is presented in Table 2.

Table 2: Comparison of computational concepts before and after the intervention (n = 39)

Computational Concepts	Pre-test <i>M (SD)</i>	Post-test <i>M (SD)</i>	<i>t</i>
Basic directions and sequences	2.90 (1.10)	3.67 (0.58)	4.74*
Loops: repeat times	2.31 (0.83)	3.38 (0.75)	8.68*
Loops: repeat until	2.00 (0.86)	3.15 (0.63)	8.87*
If: simple conditional	0.79 (0.77)	2.18 (1.07)	8.30*
If/else: complex conditional	1.31 (0.92)	2.33 (0.81)	9.58*
While conditional	0.77 (0.71)	2.05 (0.86)	11.06*
Simple functions	1.56 (1.14)	2.67 (0.96)	8.74*
Overall concepts	11.64 (2.98)	19.46 (2.35)	24.60*

Note. * $p < .001$.

Overall Performance. The findings revealed a statistically significant improvement in the students’ overall computational thinking skills. Out of a maximum score of 28, the students’ post-test mean score ($M = 19.46$, $SD = 2.35$; $range = 13–23$) was significantly higher than their pre-test mean score ($M = 11.64$, $SD = 2.98$; $range = 5–17$), with $t(38) = 24.60$, $p < .001$. This substantial increase confirms that the integration of the Engineering Design Process within an agricultural context effectively enhanced the students’ computational thinking skills.

Analysis by Computational Concepts. When analyzing the seven specific computational components, statistically significant improvements ($p < .001$) were observed across all areas:

- Basic Directions and Sequences: Students demonstrated a solid foundational understanding. The pre-test mean was 2.90 ($SD = 1.10$), which significantly increased to a near-mastery level of 3.67 ($SD = 0.58$) out of 4 points in the post-test.

- Loops (Iterative Patterns): The students' comprehension of iterative processes showed notable growth. The "Loops-repeat times" scores increased from 2.31 to 3.38, while the more complex "Loops-repeat until" scores rose from 2.00 to 3.15. This indicates that the practical activities successfully solidified their understanding of both basic and advanced repetitive patterns.
- Conditional logic (if, if/else, while): The most striking developments occurred in the application of conditional statements, which are crucial for decision-making in programming. (1) *If: simple conditional*: The baseline knowledge was initially low ($M = 0.79$), but it significantly improved post-intervention ($M = 2.18$), demonstrating the effectiveness of teaching basic conditional commands. (2) *If/else: complex conditional*: Despite the complexity, the mean score notably increased from 1.31 to 2.33, demonstrating that most learners benefited from the contextualized activities. (3) *While conditional*: This component recorded the lowest pre-test score ($M = 0.77$) but exhibited the largest improvement ($t = 11.06$), reaching a post-test mean of 2.05. The hands-on smart farming scenarios were especially effective in conveying complex control flow concepts.
- Simple functions: The ability to design modular, functional code increased from a pre-test mean of 1.56 to a post-test mean of 2.67 ($t = 8.74$). This growth highlights the students' improved capacity to manage and organize larger segments of code effectively.

In conclusion, the data demonstrate that anchoring computational concepts in tangible, real-world smart farming problems allows students to successfully grasp and apply complex programming logic, leading to significantly higher achievement in computational thinking skills.

Practical Application of Computational Thinking Skills (Performance-Based Rubric)

To triangulate and support the quantitative findings from the multiple-choice CT Concept Test (Table 2), the students' practical abilities to solve problems were evaluated using the performance-based CT assessment (rubric scoring). This instrument specifically measured the application of the four core CT pillars in authentic scenarios. Figure 2 shows the development of scores for each computational thinking skill across the four learning activities.

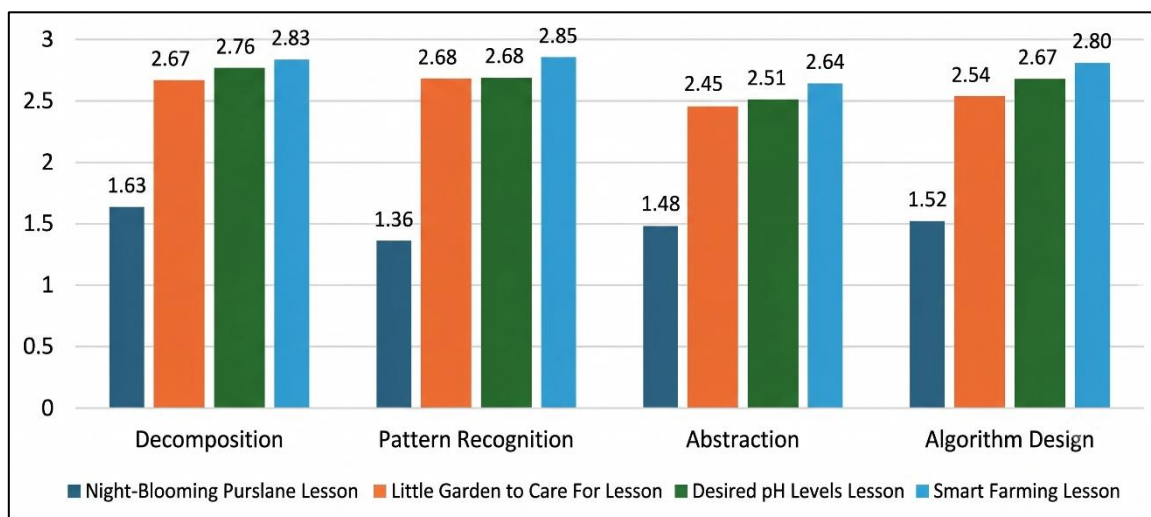


Figure 2: Development of students' computational thinking skills across four EDP-based smart farming learning activities.

Development Across CT Components

Continuous assessment during the four learning activities—Night-Blooming Purslane, Little Garden to Care For, Desired pH Levels, and Smart Farming—revealed clear progression and distinct developmental trajectories across each computational thinking component:

- **Problem Decomposition:** Students demonstrated strong, consistent development from the first activity through to the final lesson. The overall assessment indicates a high level of ability to break down complex scenarios into specific, manageable issues ($M = 2.46$, $SD = 0.56$). This is reflected in the post-test results, where 41.03% of students achieved a “Good” level and 56.41% performed at a “Moderate” level. Students successfully demonstrated this by providing precise answers to pinpoint underlying issues, such as identifying “too little or too much watering” or “yellowing plant leaves.”
- **Algorithm Design:** This component showed strong and consistent development similar to Problem Decomposition, with students continuously improving their procedural planning skills across all activities ($M = 2.38$, $SD = 0.59$). Interestingly, the post-test evaluation revealed that Algorithm Design was the component in which students demonstrated the highest proficiency. A total of 53.85% of students successfully achieved a “Good” level. This was evidenced by their ability to successfully translate their logical thinking into clear, systematic flowcharts to solve the given problems.
- **Pattern Recognition:** The developmental trajectory for this component was unique and highly distinctive. Although initial scores during the Night-Blooming Purslane lesson were noticeably low, students demonstrated the most significant adaptation and growth over time, eventually achieving the highest mastery in the final Smart Farming activity ($M = 2.38$, $SD = 0.70$). Based on the post-test responses, students effectively identified trends and grouped similar issues (28.21% achieved a “Good” level and 71.79% achieved a “Moderate” level). For instance, they effectively categorized answers like “incorrect watering” and “improper care” under the same environmental pattern.
- **Abstraction:** Students showed increasing development in filtering out irrelevant narrative details to accurately pinpoint core problems. Consequently, in the post-test evaluation, 46.15% of students achieved a “Good” level in this component. A clear example of this progression is their ability to prioritize issues, stating priorities such as “resolving the water issue,” or analyzing the context to abstract the necessity for an automated solution by identifying that the protagonist “has no time.”

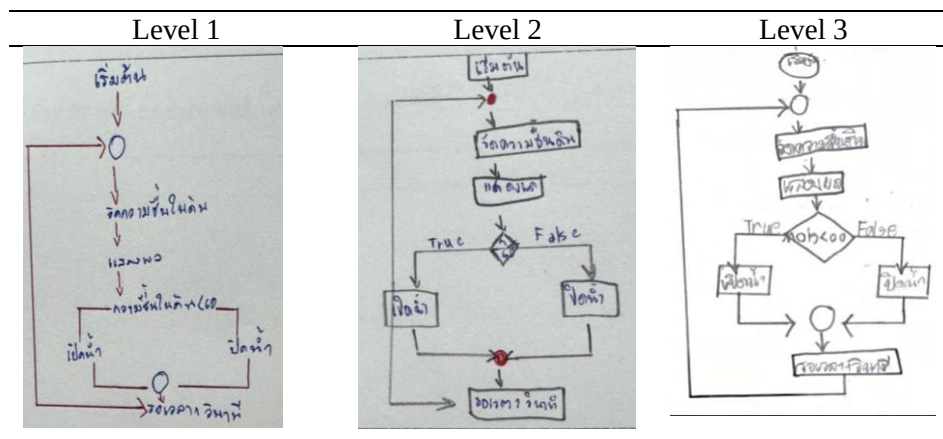


Figure 3: Examples of student flowcharts demonstrating varying levels of proficiency in algorithm design.

Based on the Algorithm Design rubric, the three student flowcharts (from left to right) illustrate distinct levels of proficiency. The left flowchart (Level 1: Fair) shows a basic understanding of the operational sequence but predominantly lacks standard flowchart symbols, omitting process rectangles and decision diamonds. It relies heavily on plain text and un-arrowsed lines at decision branches, resulting in unclear communication. The middle flowchart (Level 2: Moderate) demonstrates improved accuracy by incorporating standard symbols and clearly defining “True/False” conditional paths. However, it contains minor symbolic errors, most notably using a

process rectangle instead of a standard terminator (oval) for the “Start” state. Finally, the right flowchart (Level 3: Good) fully meets the rubric’s highest criteria. The student accurately designed the algorithm with clear, step-by-step details, employing the correct standard symbols throughout—terminators for the start state, rectangles for processes (e.g., measuring moisture, displaying data), and a decision diamond with well-defined conditional paths and a neatly organized feedback loop.

Application in Smart Farming Projects

The practical application of these CT skills was evident in the students’ final smart farming projects. Across all six collaborative groups (with project titles such as “Automated Moisture,” “Smart Plant Sensor,” and “Good Soil, Perfect Water”), the application of the four CT pillars was highly consistent. As observed in the project data, students effectively decomposed environmental factors (identifying inconsistent watering and improper humidity as sub-problems), categorized these into broader water management patterns, abstracted the core requirement (the need for automated alerts to save labor), and designed functional algorithms (e.g., *Start → Read Sensor Value → Compare with Standard → Trigger Alert/Open Water Pump → End*). This robust alignment between the rubric assessment and the final prototypes confirms that the EDP-based smart farming activities successfully enhanced both theoretical understanding and practical computational thinking skills. The implementation of these EDP-based activities yielded a significant improvement in students’ computational thinking skill scores. This finding aligns with Román-González et al. (2017) and Jatuponthianchai et al. (2022), who established that problem-solving abilities significantly impact CT development.

The success of this intervention stems from the six-step Engineering Design Process, which inherently operationalizes the four pillars of CT; from decomposing problems (Step 1) and recognizing patterns in data (Step 2), to abstracting constraints for design (Step 3) and iteratively debugging algorithms (Steps 4–6). By replacing abstract coding instruction with hands-on, student-centered prototyping, learners successfully constructed new knowledge. This approach is consistent with Samad et al. (2023), who demonstrated that integrating CT with the EDP effectively transforms students into self-reliant, reflective problem solvers capable of navigating complex STEM challenges. Furthermore, Galanti and Holincheck (2024) corroborate that aligning instructional design with EDP phases effectively builds elementary students’ CT dispositions, particularly their persistence in open-ended problem solving.

Crucially, applying the EDP within an authentic smart farming context challenged students with relatable, real-life variables (e.g., soil moisture, light). Recent research by Thipphayasaeng et al. (2024) strongly supports this conclusion, showing that utilizing smart agriculture environments to teach programming significantly enhances learners’ CT skills by grounding logical tasks in tangible, physical outcomes. Ultimately, systematic engineering challenges within agricultural contexts act as highly effective catalysts for translating theoretical computational concepts into practical 21st-century skills.

Beyond empirical consistency with prior studies, the success of this intervention can be deeply understood through multiple theoretical lenses, which explain the underlying mechanisms of how EDP promotes computational thinking. First, through the lens of constructivism, the EDP framework required students to actively construct knowledge through iterative problem solving rather than passively receiving information. When prototypes failed during the testing phase, students engaged in continuous cognitive restructuring to find solutions. Second, constructionism played a vital role; by designing and creating tangible artifacts—such as the automated irrigation systems—students materialized abstract coding syntax into physical, functional models, making the learning process highly meaningful.

Furthermore, the use of the smart farming context aligns directly with situated learning theory. Students did not learn computational thinking in a vacuum; rather, they acquired these skills within an authentic, relatable agricultural context, demonstrating how computational concepts are inextricably linked to solving real-world challenges. Finally, the instructional process effectively utilized cognitive apprenticeship. The teacher acted as a facilitator who provided initial scaffolding,

modeling, and coaching during the early stages of problem decomposition and algorithm design. As the lessons progressed, there was a gradual transfer of responsibility, culminating in the students autonomously debugging their prototypes and presenting their final smart farming outcomes. Together, these theoretical mechanisms illustrate why the integration of EDP and smart farming is highly effective in cultivating higher-order computational thinking.

CONCLUSION AND IMPLICATIONS

This study concludes that integrating the Engineering Design Process (EDP) within a smart farming context significantly enhances the computational thinking (CT) skills of fifth-grade students. The developed instructional activities successfully transformed abstract programming concepts into tangible, real-world applications. By actively engaging in the six-step EDP, ranging from identifying authentic agricultural problems, such as improper soil moisture, to designing, testing, and debugging automated sensor prototypes, students systematically practiced and mastered the four core pillars of CT: decomposition, pattern recognition, abstraction, and algorithm design. The quantitative results corroborated these gains, revealing a statistically significant improvement in both the students' theoretical understanding of computational concepts and their practical problem-solving proficiencies post-intervention.

The overarching impact of this research lies in its pedagogical contribution to primary computing and STEM education. By anchoring computational tasks in authentic agricultural scenarios, the instructional framework successfully bridged the gap between isolated coding exercises and meaningful physical outcomes. Students no longer perceived programming as a detached, screen-based activity; instead, they recognized it as a powerful, applicable tool for innovation and agricultural sustainability. Ultimately, this context-driven EDP model provides educators with a highly effective, constructivist approach to foster computational thinking, preparing young learners to confidently navigate and solve complex, multidisciplinary challenges in the future.

Despite the significant improvements observed, this study acknowledges certain methodological limitations inherent in the one-group pre-test–post-test design. Specifically, the absence of a control group exposes the findings to potential threats to internal validity, such as maturation (students' natural cognitive development over the 12-week intervention), history effects, and testing effects (such as memory bias from using identical pre- and post-test instruments). However, it should be noted that the 12-week interval between test administrations helps mitigate immediate recall bias, and the quantitative test results are strongly triangulated by the students' consistent growth in the qualitative performance-based assessments and final physical projects. While the qualitative evidence strongly links the students' progress directly to their engagement in the EDP-based smart farming activities, it is possible that these external factors partially contributed to the overall score increases. Therefore, future research should employ a controlled experimental or quasi-experimental design to more robustly isolate the effects of the instructional intervention.

Furthermore, the findings revealed distinct developmental trajectories among specific CT components; notably, pattern recognition required extended time to develop, whereas students' understanding of while conditionals improved dramatically. Future studies should investigate the cognitive factors underlying these learning curves. A clearer understanding of these processes would allow educators to design more targeted instructional scaffolding for each computational concept.

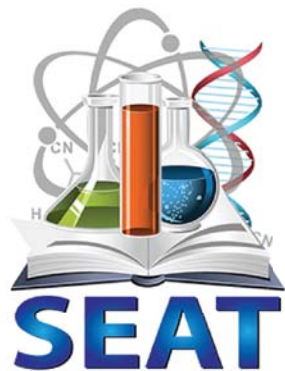
USE OF ARTIFICIAL INTELLIGENCE TOOLS

In the preparation of this manuscript, the authors utilized Gemini to assist with spelling and grammar checking, language refinement, reference formatting, and text extraction from large documents. The authors have thoroughly reviewed all AI-assisted outputs and take full responsibility for the accuracy, completeness, and intellectual integrity of the final content.

REFERENCES

- Barr, V., & Stephenson, C. (2011). Bringing computational thinking to K–12: What is involved and what is the role of the computer science education community? *ACM Inroads*, 2(1), 48–54. <https://doi.org/10.1145/1929887.1929905>
- Chalmers, C. (2018). Robotics and computational thinking in primary school. *International Journal of Child-Computer Interaction*, 17, 93–100. <https://doi.org/10.1016/j.ijcci.2018.06.005>
- El-Hamamsy, L., Zapata-Cáceres, M., Martín-Barroso, E., Mondada, F., Dehler Zufferey, J., & Bruno, B. (2022). The competent computational thinking test: Development and validation of an unplugged computational thinking test for upper primary school. *Journal of Educational Computing Research*, 60(7), 1818–1866. <https://doi.org/10.1177/07356331221081753>
- Galanti, T. M., & Holincheck, N. M. (2024). Integrating computational thinking in elementary STEM using the engineering design process. *School Science and Mathematics*, 124(4), 279–286. <https://doi.org/10.1111/ssm.12638>
- García-Peñalvo, F. J., & Mendes, A. J. (2018). Exploring the computational thinking effects in pre-university education. *Computers in Human Behavior*, 80, 407–411. <https://doi.org/10.1016/j.chb.2017.12.005>
- 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>
- Hsu, T. C., Chang, S. C., & Hung, Y. T. (2018). How to learn and how to teach computational thinking: Suggestions based on a review of the literature. *Computers & Education*, 126, 296–310. <https://doi.org/10.1016/j.compedu.2018.07.004>
- Isnaini, R., Budiyanto, C., & Widiastuti, I. (2019). Robotics-based learning to support computational thinking skills in early childhood. *AIP Conference Proceedings*, 2194(1), 020044. <https://doi.org/10.1063/1.5139776>
- Jatuponthianchai, R., Samahito, C., & Butkatanyoo, O. (2022). The effects of computational thinking learning experiences provision on problem solving ability for early childhood students. *Journal of Educational Innovation and Research*, 6(2), 366–380.
- Kareemee, S. (2017). Using the engineering design process to foster creativity and problem-solving skills (Part 1). *IPST Magazine*, 46(209), 23–27.
- Lin, S.Y., Chien, S.Y., Hsiao, C.L., Hsia, C.H., & Chao, K.M. (2020). Enhancing computational thinking capability of preschool children by game-based smart toys. *Electronic Commerce Research and Applications*, 44, Article 101011. <https://doi.org/10.1016/j.elerap.2020.101011>
- Mentzer, N., Becker, K., & Sutton, M. (2015). Engineering design thinking: High school students' performance and knowledge. *Journal of Engineering Education*, 104(4), 417–432. <https://doi.org/10.1002/jee.20105>
- Montiel, H., & Gomez-Zermeño, M. G. (2021). Educational challenges for computational thinking in K–12 education: A systematic literature review of “Scratch” as an innovative programming tool. *Computers*, 10(6), Article 69. <https://doi.org/10.3390/computers10060069>
- Moore, T. J., Glancy, A. W., Tank, K. M., Kersten, J. A., Smith, K. A., & Stohlmann, M. S. (2014). A framework for quality K–12 engineering education: Research and development. *Journal of Pre-College Engineering Education Research*, 4(1), Article 2. <https://doi.org/10.7771/2157-9288.1069>
- National Research Council. (2012). *A framework for K–12 science education: Practices, crosscutting concepts, and core ideas*. The National Academies Press. <https://doi.org/10.17226/13165>
- Paraskevopoulou-Kollia, E. A., Michalakopoulos, C. A., Zygouris, N. C., & Bagos, P. G. (2025). Computational thinking in primary and pre-school children: A systematic review of the literature. *Education Sciences*, 15(8), 985. <https://doi.org/10.3390/educsci15080985>

- Phutwatthana, N. (2018). Engineering design and biomimicry in STEM education. *STOU Education Journal*, 11(2), 31–42. https://so05.tci-thaijo.org/index.php/edjour_stou/article/view/162004
- Román-González, M., Pérez-González, J. C., & Jiménez-Fernández, C. (2017). Which cognitive abilities underlie computational thinking? Criterion validity of the Computational Thinking Test. *Computers in Human Behavior*, 72, 678–691. <https://doi.org/10.1016/j.chb.2016.08.047>
- Samad, N. A., Osman, K., & Nayan, N. A. (2023). Computational thinking through the engineering design process in chemistry education. *International Journal of Educational Methodology*, 9(4), 771–785. <https://doi.org/10.12973/ijem.9.4.771>
- Sonay, S., & Kiray, C. (2022). Engineering design process-based computational thinking abilities among brilliant and talented students. *International Journal of Advanced Science and Computer Applications*, 1(2). <https://doi.org/10.47679/ijasca.v1i2.14>
- Su, J., & Yang, W. (2023). A systematic review of integrating computational thinking in early childhood education. *Computers and Education Open*, 4, Article 100122. <https://doi.org/10.1016/j.caeo.2023.100122>
- Sutisnawati, A., Rahmawati, Y., Sumantri, M. S., & Lestari, I. (2025). A review of integration of Engineering Design Process (EDP) learning model through STEM approach in elementary schools. *EduBasic Journal: Jurnal Pendidikan Dasar*, 7(1), 129–145. <https://doi.org/10.17509/ebj.v7i1.82001>
- Thipphayasaeng, P., Piriyaawong, P., & Phanichsiti, S. (2024). Digital twins-based cognitive apprenticeship model in smart agriculture. *International Journal of Interactive Mobile Technologies*, 18(12), 72–84. <https://doi.org/10.3991/ijim.v18i12.46847>
- Weintrop, D., Beheshti, E., Horn, M., Orton, K., Jona, K., Trouille, L., & Wilensky, U. (2016). Defining computational thinking for mathematics and science classrooms. *Journal of Science Education and Technology*, 25(1), 127–147. <https://doi.org/10.1007/s10956-015-9581-5>
- Wing, J. M. (2006). Computational thinking. *Communications of the ACM*, 49(3), 33–35. <https://doi.org/10.1145/1118178.1118215>
- Yadav, A., Hong, H., & Stephenson, C. (2016). Computational thinking for all: Pedagogical approaches to embedding 21st century problem solving in K–12 classrooms. *TechTrends*, 60(6), 565–568. <https://doi.org/10.1007/s11528-016-0087-7>



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