



EMBEDDING ANALYTICAL THINKING IN MOTION KINEMATICS: ARDUINO TIMING SENSORS IN PREDICT-OBSERVE-EXPLAIN INSTRUCTION

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ABSTRACT

Physics education in resource-limited contexts faces a persistent dual challenge, namely a shortage of affordable, high-precision laboratory equipment and an instructional culture that privileges rote memorization over genuine higher-order thinking. This gap is particularly acute in rural Thai schools, where students consistently underperform on national science assessments. This study investigates the impact of integrating affordable Arduino-based sensors with Predict-Observe-Explain (POE) instruction on the development of analytical thinking among ninety-four Grade 10 students from six rural schools in Nakhon Phanom, Thailand, and on their satisfaction with that instruction. The study employed a convergent mixed-methods design, combining a one-group pretest-posttest quasi-experimental structure with directed qualitative content analysis, implemented through a twelve-hour intervention across four motion kinematics concepts. Analytical thinking was assessed using the Mixed-Methods Analytical Thinking Test (MM-ATT), a validated 30-item instrument aligned with Marzano's New Taxonomy and covering classification, categorization, error analysis, generalization, and specification, and satisfaction was measured with a 15-item questionnaire spanning learning process quality, innovation characteristics, and perceived learning outcomes. Quantitative results showed a statistically significant improvement in analytical thinking (paired $t = -21.23$, $p < .001$), with a very large effect size (Cohen's $d = 2.01$, 95% CI [1.77, 2.32]) and a moderate normalized gain ($g = 0.32$). Qualitative analysis of student artifacts documented a structural cognitive shift from rote memorization and tautological reasoning toward evidence-based diagnosis and mathematical modeling. Satisfaction ratings placed the experience at the highest level, with the clarity afforded by the Observation phase rated highest of all items. Embedding an affordable Arduino timing sensor within POE instruction therefore develops analytical thinking across all five dimensions and is well received by students, although the twelve-hour sequence proved insufficient for most to transfer kinematic principles to novel contexts. Affordable open-source technology embedded within a theoretically grounded constructivist framework offers a scalable model for physics education in resource-constrained settings.

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Keywords: analytical thinking; Arduino timing sensor; motion kinematics; Predict-Observe-Explain instruction; resource-constrained education

INTRODUCTION

Physics education globally confronts a persistent crisis in which students demonstrate surface-level memorization without genuine conceptual understanding. International assess-

ments consistently reveal that students execute algorithmic procedures while lacking the analytical reasoning required to transfer knowledge to novel contexts (Capps et al., 2012; Pellegrino & Hilton, 2012; Voogt & Roblin, 2012; Docktor & Mestre, 2014; Osborne, 2014; Henderson et al., 2015; OECD, 2023; Andrin & Adlaon, 2026).

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This pattern is particularly acute in foundational topics such as motion kinematics, the conceptual gateway to classical mechanics. Students routinely struggle to translate abstract mathematical representations of position, velocity, and acceleration into coherent physical realities (Pellegrino & Hilton, 2012; Voogt & Roblin, 2012).

PISA 2022 data quantify the urgency of this challenge: Thailand ranked 64th out of 81 participating nations in science literacy, with over 63% of Thai students failing to meet even the minimum proficiency threshold (OECD, 2023). In rural Nakhon Phanom Province, where six Mekong River schools participated in the present study, Ordinary National Education Test (O-NET) science scores averaged 27.4% over the past three academic years (National Institute of Educational Testing Service, 2022), a figure markedly below the national mean of 30.1%. These convergent national and local indicators underscore the acute need for evidence-based pedagogical intervention in underserved rural communities. Comparable regional evidence reports markedly low levels of science literacy among junior high school students and attributes this to content-focused instruction conducted without inquiry or hands-on experimentation (Kadir et al., 2025). Neither instrument, however, directly assesses analytical thinking. PISA measures science literacy, and O-NET measures curricular achievement; neither is designed to capture cognitive operations such as classification, categorization, error analysis, generalization, and specification. The analytical thinking of students in the target schools therefore could not be established from existing data.

These challenges are even more severe in resource-constrained educational settings, where two systemic constraints converge to undermine effective physics instruction. First, prohibitive equipment costs limit access to precision scientific tools, forcing teachers to rely on manual measurement instruments such as stopwatches and ticker-tape timers that lack the precision needed to generate unambiguous empirical data for genuine conceptual engagement (Mangarin & Macayana, 2024). Second, entrenched teacher-centered pedagogical traditions relegate students to passive recipients of transmitted information, a model fundamentally inconsistent with constructivist principles of active knowledge construction (Piaget, 1973; Vygotsky, 1978; Henderson et al., 2015; Sutaphan & Yuenyong, 2019). To provide the baseline that those indicators could not, a preliminary investigation was conducted across three of the six participating schools. This comprised

semi-structured interviews with the physics teachers responsible for Grade 10 mechanics in those schools, together with a trial administration of the study's analytical thinking instrument to 45 Grade 10 students. Teachers in all three schools reported that no experimental work on motion kinematics had been undertaken and that no functional laboratory apparatus was available; instruction was delivered through lecture and worked problems. In the instrument trial, most students could reproduce the relevant kinematic formulae but could not construct or interpret a position-time graph or explain what such a graph represented. This evidence establishes the urgent pedagogical need for an affordable, inquiry-based intervention in these classrooms (Bano et al., 2018; Suárez et al., 2018; Urdanivia Alarcon et al., 2023; Casado-Mansilla et al., 2023; Mahdianur, 2025).

Constructivist learning theory advocates for active knowledge construction through iterative cycles of prediction, empirical observation, and reflective explanation (Hmelo-Silver et al., 2007; Piaget, 1973; Vygotsky, 1978). This theoretical foundation directly informs the Predict-Observe-Explain (POE) instructional strategy. Within the POE framework, learners first generate explicit written predictions grounded in their existing mental models, then systematically observe physical phenomena through controlled experimentation, and finally reconcile inconsistencies between anticipated and actual outcomes through collaborative explanation (Liew & Treagust, 1995; Coştu et al., 2012; Cinici & Demir, 2013). This deliberate creation of cognitive conflict compels learners to confront embedded misconceptions and reconstruct knowledge on more scientifically accurate foundations (Coştu et al., 2012; Henderson et al., 2015; Berek et al., 2016). Comparative studies have confirmed that POE instruction yields superior conceptual gains and more effective remediation of prior misconceptions than traditional lecture-based approaches (Forbes et al., 2020; Permatasari et al., 2023; Trisnayanti et al., 2023; Gyeltshen & Wangchuk, 2026). A meta-analysis of POE studies in science education reports a positive overall effect on achievement, indicating that this advantage holds across contexts rather than being confined to individual trials (Koyunlu Ünlü, 2024).

However, the pedagogical efficacy of the POE cycle depends critically on the clarity and precision of the observation phase. When observations are constrained by imprecise manual measurement tools, the resulting cognitive conflict weakens, allowing students to dismiss

contradictory data as experimental error rather than restructuring their prior conceptions. This is precisely where open-source Arduino micro-controllers offer a transformative pedagogical advantage, providing programmable, millisecond-precision measurement capabilities with real-time data visualization at costs representing five to fifteen percent of commercially equivalent equipment (Kubínová & Šlégr, 2015; Bouquet et al., 2017; García-Tudela & Marín-Marín, 2023; Ga & Chang, 2025; Zhao, 2026). Beyond cost-effectiveness, these devices function as cognitive amplifiers, providing the empirical evidence needed to compel genuine conceptual reconstruction within the POE framework (Mishra & Koehler, 2006; Chou, 2018; Parno et al., 2020; Pahrudin et al., 2021). The mechanism is not merely theoretical. A meta-analysis of 218 studies involving 18,051 students found cognitive conflict to be the most effective major conceptual change strategy, with Hedges' $g = 1.10$ (Pacaci et al., 2024), supporting the claim that the quality of the evidence presented during observation governs the depth of the conceptual change that follows.

Despite this potential, critical gaps remain in the literature. A systematic review by García-Tudela and Marín-Marín (2023) examined 47 Arduino-in-education studies and found that only 12% employed a theoretically grounded instructional framework, while no study specifically targeted multidimensional higher-order thinking as the primary outcome. A review by Suárez et al. (2018) covering 89 mobile inquiry-based learning studies similarly found that higher-order cognitive outcomes such as analytical thinking remained poorly operationalized. Ga and Chang (2025) further confirmed that while Arduino devices demonstrate research-grade precision at a fraction of commercial costs, the pedagogical models embedding this technology remain theoretically underdeveloped.

Therefore, this study addresses these critical gaps by situating an Arduino-POE intervention within the resource-constrained rural schools of Thailand's Mekong River region. It aims to determine whether embedding an affordable Arduino timing sensor within POE instruction develops the five dimensions of analytical thinking outlined in Marzano's New Taxonomy (2001), and whether students find that instruction acceptable in that setting. Two objectives follow. The first is to measure the effect of the Arduino-POE intervention on each of the five analytical thinking dimensions. Alongside that measurement, the study characterizes the cognitive shift underlying any observed change. The second objective

is to determine students' satisfaction with the Arduino-POE learning experience. These objectives are pursued through two research questions. (RQ1) To what extent does the Arduino-POE intervention enhance Grade 10 students' analytical thinking across Marzano's five cognitive dimensions? (RQ2) What are students' satisfaction levels with the Arduino-POE learning experience? A convergent mixed-methods approach, integrating statistical quantification of cognitive gains with qualitative analysis of cognitive transitions, is used to answer these questions, with the intention of providing an empirically validated, scalable, and replicable pedagogical model for comparable resource-constrained settings. Four delimitations bound the study: participants are limited to Grade 10 students from six rural schools in Nakhon Phanom Province; the intervention is confined to four motion kinematics topics within a 12-hour instructional sequence; analytical thinking is operationalized exclusively through Marzano's five-dimensional taxonomy; the study employs an exploratory one-group quasi-experimental design from which causal generalizations cannot be made.

METHODS

Guided by a pragmatic paradigm (Morgan, 2014), this study employs a convergent mixed-methods design (Creswell & Plano Clark, 2018) integrating a one-group pretest-posttest quasi-experimental structure (Creswell & Guetterman, 2019). This design was selected for three pragmatic reasons aligned with the study's exploratory purpose. First, implementing randomized controlled trials across six geographically dispersed rural schools poses substantial logistical and ethical challenges, as withholding a potentially beneficial intervention from a disadvantaged student population raises significant equity concerns. Second, as an exploratory proof of concept, the one-group design is appropriate for establishing implementation feasibility and generating preliminary effect size estimates to inform future large-scale randomized inquiries. Third, no prior study has examined Arduino-POE integration for analytical thinking in this context, precluding *a priori* power calculations required for a controlled trial. The study's findings are therefore interpreted as preliminary, hypothesis-generating evidence rather than definitive causal claims.

Research Procedure

The study was conducted in six sequential stages, each with a distinct purpose, procedure,

and analytical methods, as illustrated in Figure 1, and administered under standardized conditions

consistent with Creswell and Guetterman's (2019) guidelines for pre-post paired measurement.

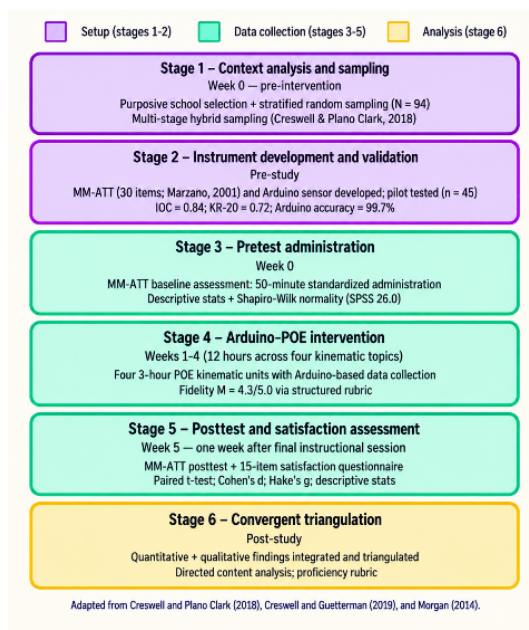


Figure 1. Six-Stage Research Procedure

Fidelity of implementation was monitored throughout the intervention via a four-criterion structured rubric (Gopalan et al., 2020): (1) written predictions elicited before any technology use, (2) Arduino data collection preceding the Explanation phase, (3) structured group discussion of prediction-observation inconsistencies, and (4) completion of all POE phases within a fixed time, yielding a mean fidelity rating of $M = 4.3/5.0$ ($SD = 0.4$).

Participants and Research Setting

The study involved 94 Grade 10 students (aged 15-16; 52 female, 42 male) from secondary schools along the Mekong River in Nakhon Phanom, Thailand. Through multi-stage hybrid sampling, schools were purposively selected based on enrollment, available laboratory facilities, and geographic accessibility. These remote institutions face persistent academic challenges, with O-NET science scores consistently falling below the national mean (National Institute of Educational Testing Service, 2022). Although these schools have general science laboratories, they lack specialized physics tools like precision timers because of budgetary constraints typical of remote Thai schools. We randomly selected one classroom per school, then used stratified random sampling to select the final 94 partici-

pants, reflecting the gender proportionality of the 178 eligible students. The remaining 84 eligible students continued their regular classroom instruction. No students were excluded based on academic performance, behavior, or any other criterion, minimizing selection bias. Post-hoc power analysis via G*Power 3.1 (Faul et al., 2007) confirmed sample adequacy. With an anticipated large effect size, the 94 participants provided a statistical power exceeding 0.99, surpassing the 64-participant threshold for exploratory research (Cohen et al., 2017).

Development of the Arduino-Based Timing Sensor for Motion Kinematics

In this design, the Arduino-based timing sensor is not an instructional medium through which content is delivered to students. It is the measurement instrument that supplies the evidential basis of the Observation phase. The design requirement follows directly from this role. The device must resolve the motion intervals under study with an uncertainty small enough that any discrepancy between a student's prediction and the recorded data cannot plausibly be attributed to the apparatus's limitations. The four development benchmarks specified below were derived from this requirement.



Figure 2. The Arduino-Based Motion-Timing Sensor: Experimental Setup

The motion-timing sensor was developed through an iterative process to meet these four standard laboratory benchmarks: millisecond precision, reliability, usability, and cost-effectiveness. The final instrument (Figure 2) features a 100-cm vertical wooden frame equipped with an adjustable sensing array. Two E18-D80NK infrared sensors (response time below 2 ms) detect the object's passage, while a solenoid electromagnet ensures a precise, zero-velocity release for free-fall experiments. The control unit's core is an ESP32-WROOM-32 microcontroller (240 MHz), chosen for its high processing speed.

The object's passage triggers the first sensor to start the timer (t_1) and the second sensor to halt it (t_2). The precise time interval is immediately displayed on the OLED screen, providing the data students need to plot displacement-time graphs and calculate gravitational acceleration (g).

Rigorous validation against a commercial Vernier Photogate ($n = 50$ trials) demonstrated an accuracy of 99.7% with a mean deviation of

only 0.003 seconds ($SD = 0.001$). The coefficient of variation remained below 0.5%, confirming the device performs comparably to professional-grade equipment. This level of resolution is more than an order of magnitude finer than the ± 0.1 s uncertainty characteristic of manual start-and-stop timing (Faux & Godolphin, 2019). This margin lets the recorded data enter the Explanation phase as evidence rather than a contested approximation. The total material cost per unit is 23.50 USD, approximately 6% of the cost of functionally equivalent commercial tools (380 USD), consistent with the low-cost principle established in prior Arduino-based educational tool development (Bouquet et al., 2017). Three experts also reviewed the innovation using the Index of Item-Objective Congruence (IOC), achieving a score of .86, indicating excellent suitability for classroom implementation.

The Integrated Arduino-POE Instructional Design

The pedagogical architecture integrated technology, pedagogy, and content knowledge (Mishra & Koehler, 2006), wherein the POE cycle served as the primary mechanism for both conceptual instruction and data generation. Each phase of the Arduino-integrated POE sequence targeted distinct dimensions of Marzano's (2001) analytical thinking taxonomy. Within that cycle, the Arduino sensors functioned as cognitive amplifiers (Parno et al., 2020), supplying evidence precise enough to compel students to confront the discrepancy between prediction and observation rather than dismiss it. Table 1 details how Arduino-based data collection was integrated into each POE phase and which analytical thinking dimensions each phase was designed to elicit.

Table 1. The Pedagogical Framework for Arduino-Integrated POE Instruction

POE Stage	Student Action and Instructional Activities	Role of Arduino Technology	Target Analytical Thinking (Marzano's Taxonomy)
Phase 1 Prediction (Induction of Cognitive Conflict)	During the initial lesson, student groups of 3-4 members are presented with a specific kinematics scenario and required to formulate explicit, written predictions of the expected outcomes and to sketch anticipated graphs (e.g., position vs. time) based on their prior knowledge and understanding.	No technology is used just yet in this phase. The absence of technology is deliberate to ensure predictions come purely from students' existing mental models and prior knowledge rather than observed data.	Classification and Categorization Students draw on prior knowledge to identify relevant variables and organize the type of motion into a structure before committing to a prediction.

POE Stage	Student Action and Instructional Activities	Role of Arduino Technology	Target Analytical Thinking (Marzano's Taxonomy)
Phase 2 Observation (High-Precision Empirical Engagement)	Students run the physical experiment and watch the motion data graphed in real time on the screen as the event occurs, comparing the recorded data with their initial sketched predictions.	Cognitive amplifier and data generator: Arduino sensors provide immediate millisecond-precision visualization of abstract kinematic concepts. It supplies the undeniable empirical evidence needed to challenge flawed predictions.	Error Analysis The precision of the recorded data pushes the discrepancy between prediction and observation beyond experimental error and requires students to diagnose its source.
Phase 3 Explanation (Analytical Synthesis and Reconstruction)	Students collaboratively discuss discrepancies between their initial predictions and the recorded empirical data and construct a scientifically grounded argument explaining why the motion occurred as recorded, revising their initial rules.	Evidence verification: The recorded Arduino data serves as the objective baseline for student debates, with graphical features such as slopes and curves used to justify revised explanations.	Generalization and Specification Students abstract kinematic rules from the observed data patterns and specify how these rules apply to contexts beyond the experiment.

Note. Table 2 provides operational definitions of the five dimensions.

The first author facilitated all sessions across the six school sites to minimize teacher-variance confounds, and implementation fidelity was monitored through structured observation protocols and reflective video analysis.

Research Instruments

To facilitate a robust convergent mixed-methods analysis, the instrumentation was designed to capture both quantifiable performance metrics and descriptive cognitive processes (Morgan, 2014).

The Mixed-Methods Analytical Thinking Test (MM-ATT)

The primary instrument was a custom-developed 30-item test aligned with Marzano's New Taxonomy of Educational Objectives (Marzano, 2001), with six items per dimension (Classification, Categorization, Error Analysis, Generalization, Specification). Items were constructed in an

open-ended format adapted from standardized physics examination questions, allowing students to express underlying reasoning rather than providing simple numerical answers. The items were structured around a common experimental scenario involving measuring an object's motion at constant velocity using the Arduino timing sensor, ensuring authentic alignment between the intervention and assessment context. Following data collection using the Arduino sensors, students were prompted to analyze their findings through the following qualitative lenses: (1) Identify independent and dependent variables (Classification); (2) Organize data into graphs and link them to the equation $\Delta x = ut + \frac{1}{2}at^2$ (Categorization); (3) Analyze the impact of ± 0.1 m positional uncertainty (Error Analysis); (4) Summarize data-driven relationships versus initial predictions (Generalization); (5) Design a real-life village speed-monitoring system (Specification).

Table 2. Operational Definitions of the Five Analytical Thinking Dimensions in the Motion Kinematics Context

Dimension	Operational Definition (Marzano, 2001; Marzano & Kendall, 2007)	Observable Student Performance in This Study
Classification (Marzano's matching)	Identifying the fundamental elements of a phenomenon and distinguishing essential features from irrelevant ones	Identifies time (s) as the independent variable and position (m) as the dependent variable; articulates the graphical parameters that define constant velocity
Categorization (Marzano's classifying)	Organizing data into appropriate structures and linking observed patterns to established scientific concepts	Plots position-time data; interprets the slope as velocity and deductively reduces $\Delta x = ut + \frac{1}{2}at^2$ to $s = vt$ when $a = 0$
Error Analysis (Marzano's analyzing errors)	Identifying and diagnosing errors, evaluating the propagation of measurement uncertainty, and determining the root cause of variance	Computes the propagation of a ± 0.1 m positional uncertainty into velocity ($\pm 0.1/\Delta t$ m/s); hypothesizes multiple physical sources for an unexpected non-linear graph

Generalization (Marzano's generalizing)	Inferring a governing principle from observed data and extending it beyond the observed instance	Identifies a linear position-time graph as evidence of constant velocity and connects this pattern to the initial prediction
Specification (Marzano's specifying)	Applying a generalized principle to predict or design within a novel, specific situation	Designs a functional speed-monitoring system, specifying sensor placement, timing logic, and the velocity calculation

Note. Definitions adapted from Marzano (2001) and Marzano and Kendall (2007). MM-ATT items were constructed to elicit the performances specified in column three; the same definitions served as an a priori coding frame for the directed content analysis. The POE phase in which each dimension is primarily elicited is given in Table 1.

Content validity was established through expert review by three physics education specialists, yielding a mean Item-Objective Congruence (IOC) of .84. Reliability was established via pilot testing with 45 non-participating Grade 10 students, yielding a Kuder-Richardson Formula 20 (KR-20) coefficient of .72, an acceptable value for dichotomously scored higher-order thinking assessments (Tavakol & Dennick, 2011).

The standard error of measurement (SEM) was 2.51. Item analysis yielded a mean difficulty index of $p = .73$ and a mean discrimination index of $r = .52$, confirming robust capacity to differentiate proficiency levels (High, Partial, Limited). Proficiency-level coding used a consensus-based process in which two raters independently reviewed a subset of responses, discussed discrepancies, and agreed on final classifications before full-scale analysis.

Student Satisfaction Questionnaire

Student satisfaction was evaluated via a 15-item, five-point Likert-scale questionnaire (ranging from 1 for lowest satisfaction to 5 for highest) organized into three subscales: (1) Learning Process Quality (five items focusing on the experience of the POE phases and collaborative

learning dynamics), (2) Innovation Characteristics (five items evaluating the functional usability of the Arduino system and the perceived reliability of its digital measurements), and (3) Perceived Learning Outcomes (five items assessing students' self-reported growth in conceptual understanding and analytical skill development).

Content validity was established through expert review, producing a mean IOC of .79. Internal consistency reliability yielded a Cronbach's alpha coefficient of .76, indicating acceptable consistency for an affective measure (Taber, 2018). The questionnaire was administered immediately following the posttest to capture perceptions while the learning experience remained salient.

Data Analysis Procedures

The analytical strategy adhered to a convergent mixed-methods framework in which quantitative results were systematically triangulated with qualitative evidence to provide a comprehensive portrait of students' analytical development. Table 3 presents the explicit alignment between each research instrument and its corresponding analytical technique.

Table 3. Instrument-to-Analysis Alignment Matrix

Instrument	Data Type	Analytical Technique	Research Question
MM-ATT; 30-item scored responses	Quantitative	Paired-samples t-test, Cohen's d, Hake's g	RQ1
MM-ATT; open-ended written responses	Qualitative	Directed content analysis, Marzano (2001) mapping, Jonsson and Svengby (2007) rubric	RQ1
Satisfaction Questionnaire; 15-item Likert	Quantitative	Descriptive statistics (M, SD, 95% CI)	RQ2
Arduino sensor data logs	Objective anchor	Triangulation baseline for qualitative artifact evaluation	RQ1 & RQ2

Quantitative Analysis

Statistical processing was accomplished via SPSS 26.0. Shapiro-Wilk normality tests, along with visual inspections of histograms and Q-Q plots, confirmed that pretest, posttest, and

gain scores followed a normal distribution ($p > .05$), with zero attrition ($N = 94$).

To address Research Question 1, we compared pretest and posttest mean scores using paired-samples t-tests, consistent with guidelines for

within-group repeated-measures designs (Cohen et al., 2017). Practical significance was quantified using Cohen's *d*, calculated as the difference between posttest and pretest means divided by the pooled standard deviation, with 95% confidence intervals estimated via bootstrapping in SPSS 26.0. Effect magnitude was interpreted according to conventional benchmarks of small ($d = 0.20$), medium ($d = 0.50$), and large ($d = 0.80$). The observed pretest-posttest correlation ($r = .66$) was noted as a contributing factor to the magnitude of Cohen's *d*, given the well-documented sensitivity of paired-design effect sizes to testing and Hawthorne effects (Furtak et al., 2012; McCambridge et al., 2014).

To provide a more conservative and context-sensitive indicator of learning gain, Hake's (1998) normalized gain was calculated and interpreted as low ($g < 0.30$), moderate ($0.30 \leq g < 0.70$), or high ($g \geq 0.70$). To control the family-wise error rate across six simultaneous statistical comparisons (comprising the overall composite score and each of the five analytical thinking sub-dimensions), a Bonferroni correction was applied, setting the adjusted significance threshold at $\alpha = .008$.

To address Research Question 2, student satisfaction levels were examined through descriptive statistics, with dimension and item means interpreted against the following established benchmarks: 2.50 or below (low satisfaction), 2.51 to 3.50 (moderate), 3.51 to 4.50 (high), and above 4.50 (highest satisfaction), consistent with widely adopted Likert interpretation criteria in educational research (Tavakol & Dennick, 2011; Taber, 2018).

Qualitative Analysis

Data derived from open-ended reasoning prompts were analyzed via directed content analysis (Hsieh & Shannon, 2005), a method appropriate when existing theory provides an established categorical framework for organizing and interpreting qualitative data. Marzano's (2001) five analytical dimensions served as an a priori coding framework, with response segments systematically mapped onto Classification, Categorization, Error Analysis, Generalization, and Specification. A three-stage coding protocol adapted from Morgan (2014) and Jonsson and Svingby (2007) was employed to elaborate upon the statistical findings.

Stage 1 Directed Coding: Student responses were reviewed, and segments were identified as instances of reasoning relevant to each of Marzano's five analytical dimensions, using the operational definitions derived from the taxonomy as coding criteria.

Stage 2 Categorization: Segments were mapped onto Marzano's five cognitive dimensions to provide thick description of the cognitive shifts occurring across the intervention.

Stage 3 Rubric-Based Leveling: Reasoning was categorized into proficiency levels (High, Partial, or Limited) to provide descriptive evidence of the cognitive shifts reflected in the t-test results (Jonsson & Svingby, 2007). This qualitative component triangulates the data, providing "thick description" of how the Arduino-POE intervention facilitated the transition from rote memorization to scientific analysis.

Arduino sensor data logs served not as a scored instrument but as an objective empirical anchor, ensuring that students' qualitative reasoning artifacts were evaluated against verifiable observational records rather than unsubstantiated claims.

Ethical Considerations

The study procedure received approval from Nakhon Phanom University Ethics Committee in Human Research, Thailand (Ethics Review Process Number: HE120/68), based on the Declaration of Helsinki and the ICH Good Clinical Practice Guideline. All participating students provided informed assent after a developmentally appropriate explanation of the research purposes, procedures, and rights. Parents or legal guardians provided written informed consent authorizing student participation and data collection. The researchers maintained participant confidentiality by assigning unique numerical identifiers to replace personally identifying information in all datasets and research reports. All data are stored securely with access restricted to authorized research team members.

RESULTS AND DISCUSSION

Quantitative Efficacy of the Analytical Thinking Performance

Table 4 presents the pretest, posttest, inferential statistics, and learning gain indicators for all five analytical thinking dimensions and the overall composite score ($N = 94$).

Table 4. Pretest, Posttest, *t*-test, and N-Gain for Analytical Thinking (N = 94)

Cognitive Dimension	Max Score	Pretest M (SD)	Posttest M (SD)	<i>t</i> -value	<i>p</i> -value	Cohen's <i>d</i>	95% CI	N-Gain (<i>g</i>)	Gain Criteria
Classification	6	1.81 (0.64)	3.16 (0.85)	-17.28	<.001*	1.80	[1.57, 2.10]	0.32	Moderate
Categorization	6	2.17 (0.67)	3.68 (0.99)	-16.94	<.001*	1.80	[1.55, 2.11]	0.39	Moderate
Error Analysis	6	1.87 (0.68)	3.30 (0.88)	-15.39	<.001*	1.82	[1.57, 2.13]	0.35	Moderate
Generalization	6	1.71 (0.58)	2.82 (0.82)	-14.22	<.001*	1.56	[1.33, 1.86]	0.26	Low
Specification	6	1.85 (0.85)	2.96 (1.16)	-8.97	<.001*	1.08	[0.84, 1.37]	0.27	Low
Overall composite	30	9.41 (2.36)	15.91 (3.92)	-21.23	<.001*	2.01	[1.77, 2.32]	0.32	Moderate

Note. **p* < .001 indicates statistical significance after Bonferroni correction ($\alpha = .008$)

The Arduino-POE intervention produced statistically significant improvements across all five analytical thinking dimensions and the overall composite score. The overall effect size ($d = 2.01$) is very large and substantially exceeds the educational research median of $d = 0.40$ (Cheung & Slavin, 2016), while the moderate normalized gain ($g = 0.32$) provides a more conservative and contextually informative indicator of cognitive improvement. As Hake's g is less sensitive to floor effects than Cohen's d (Hake, 1998), the moderate gain is consistent with meta-analytic evidence that short-duration inquiry-based learning (IBL) interventions, typically one to four weeks in duration, produce lower effect sizes than longer programs, and that substantial gains in higher-order thinking generally require sustained instructional exposure beyond four weeks (Prayogi et al., 2022; Antonio & Prudente, 2024; Arifin et al., 2025).

Dimension-specific analysis reveals two distinct tiers of effect size. Error Analysis ($d = 1.82$), Classification ($d = 1.80$), and Categorization ($d = 1.80$) cluster closely together at the upper level, while Generalization ($d = 1.56$) and Specification ($d = 1.08$) fall below them, with the confidence interval for Specification lying entirely below those of the three upper dimensions.

The near-floor pretest means ($9.41/30 = 31.4\%$) are acknowledged as a factor known to

mathematically amplify paired-design effect sizes through restriction-of-range effects, independent of genuine learning. The absence of a control group limits causal attribution and raises concerns regarding maturation, testing, and Hawthorne effects (Furtak et al., 2012; McCambridge et al., 2014). For comparative context, controlled studies using POE instruction (Coştu et al., 2012) and inquiry-based physics interventions (Parno et al., 2020) each reported $d \approx 0.68$, suggesting a plausible true intervention effect in the range of $d = 0.80$ to 1.20 . Notwithstanding these interpretive cautions, the qualitative evidence presented below triangulates the quantitative data, confirming that genuine cognitive restructuring occurred beyond floor-driven statistical amplification and that these results constitute meaningful preliminary evidence warranting future randomized controlled trials (Gopalan et al., 2020; Lortie-Forgues & Inglis, 2019).

While Table 4 quantifies the magnitude of improvement through inferential statistics, Figure 3 provides a qualitatively distinct picture by mapping the distribution of individual students across three proficiency levels, information that mean scores structurally cannot convey, particularly regarding the proportion of students still at Limited proficiency after intervention.

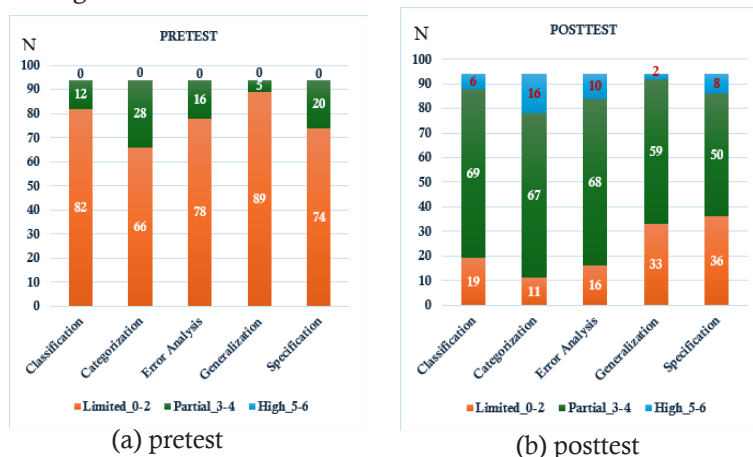


Figure 3. Distribution of Student Analytical Thinking Proficiency Levels Across Five Dimensions: (a) Pretest and (b) Posttest

Note. Bars show the number of students at each proficiency level. High = score 5-6; Partial = score 3-4; Limited = score 0-2 (out of a maximum of 6 per dimension).

Counts were derived directly from raw student scores (N = 94).

The pretest data revealed a uniformly limited baseline. No student achieved High proficiency in any dimension prior to the intervention. The vast majority were concentrated at the Limited level, ranging from 70.2% (Categorization) to 94.7% (Generalization), fully consistent with the near-floor composite pretest mean (9.41/30) in Table 4. Prayogi et al. (2022) report a strikingly parallel baseline in which both their experimental and control groups scored at the least critical level across all cognitive indicators at pretest, reinforcing that near-floor starting points are a recurring feature of studies targeting higher-order thinking in resource-typical science classrooms rather than an artifact unique to the present study.

Post-intervention, the proficiency distribution shifted substantially across all dimensions. The most pronounced movement into High proficiency occurred in Categorization (0.0% to 17.0%), followed by Error Analysis (0.0% to 10.6%), consistent with those dimensions sitting in the upper cluster of effect sizes in Table 4. The shift away from Limited proficiency was most dramatic in Classification (−67.0%) and Error Analysis (−66.0%). Critically, however, Specification retained the highest posttest Limited rate (38.3%) alongside the smallest shift into Partial proficiency (+31.9%), while Generalization retained the second-highest posttest Limited rate (35.1%) and the lowest posttest High rate (2.1%).

This proficiency-level evidence corroborates the normalized gain pattern in Table 4. The two highest-order dimensions retained the largest proportions of students at Limited proficiency post-intervention, confirming that a 12-hour sequence is insufficient for full mastery of principle extraction and knowledge transfer, a pattern consistent with Öztürk et al.'s (2022) finding that higher-order cognitive outcomes require more sustained instructional exposure.

Qualitative Manifestation of Analytical Thinking

The qualitative analysis examines students' reasoning artifacts across Marzano's five cognitive dimensions, providing the thick description necessary to confirm whether the quantitative gains reflect genuine cognitive restructuring or surface-level recall improvement. The analysis centers on a core experimental scenario in which students used the Arduino-based timing sensor to measure the motion of an object at constant velocity, with time (t) as the independent variable and position (s) as the dependent variable. The five dimensions are reported in the sequence in which the POE cycle elicited them, from the predictions made in

Phase 1 to the transfer task at the close of Phase 3, with the phase-by-dimension mapping set out in Table 1.

1. Classification: Discerning Variables and Characteristics

In the motion kinematics experiment, students were required to identify experimental variables and articulate the graphical parameters characterizing "constant velocity".

Identification of Variables: Analysis revealed a marked shift in how students conceptualized the experimental framework. At pretest, students demonstrated a fundamental lack of theoretical framework. Most students failed to identify the investigation's structure, leaving responses blank or citing irrelevant factors. In posttest artifacts, most students (73.4%) progressed to Partial-proficiency by correctly naming time and position as variables without articulating their roles within the experimental structure, while a subset demonstrated High-proficiency reasoning. Student S25, for instance, correctly distinguished the parameters:

"The independent variable is time (s) and the dependent variable is position (m)." (S25)

Attribute Identification: In the pretest, students failed to establish the theoretical connection between the position-time graph and physical motion. They merely labeled arithmetic patterns as constant velocity without further justification (e.g., "the [position] increases 2 meters every 1 minute [sic]").

While Partial-proficiency posttest responses recognized the graph's linearity as an attribution of constant velocity, they did not fully connect slope to physical meaning. High-proficiency responses, by contrast, demonstrated deeper analytical reasoning. Student S25 explicitly linked the data's linearity to the physical concept:

"For an object moving at a constant velocity, the position-time graph is a straight line with a constant positive slope. This indicates that the object's position changes uniformly over time, and the slope of the graph is equal to the object's velocity." (S25)

2. Categorization: Linking Data to Physical Theory

The assessment examined two key areas: the ability to interpret graphical representations of motion data and the ability to link experimental findings deductively to kinematic equations.

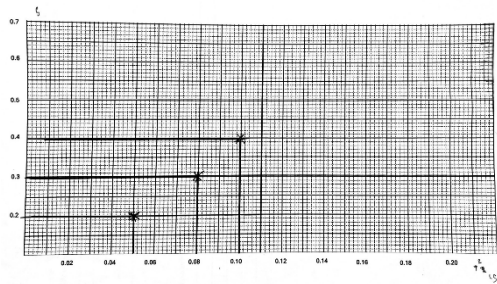
Graphical Organization: Initial assessments indicated that while students could plot coord-

dinate points (Figure 4a), they struggled to extract physical meaning from the data structure and often failed to interpret the significance of the slope.

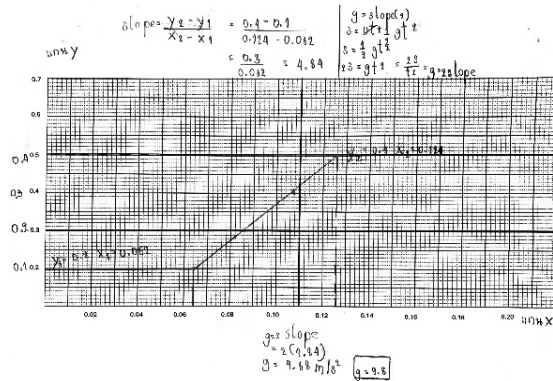
Post-intervention analysis revealed a collective shift. Most students (71.3%) reached Partial proficiency, successfully identifying the graph's geometric attribute (a straight line) even when slope calculations remained incomplete, but without connecting slope to velocity. High-

performing students moved beyond simple plotting to explicitly connect mathematical slope to physical constants. Student S54, for example, correctly identified the linear relationship and explicitly linked the mathematical slope to the physical concept of constant velocity (Figure 4b).

"Data: (0,0), (1,2), (2,4), (3,6), (4,8). The graph is linear and passes through the origin; therefore, the slope represents a constant velocity of 2 m/s." (S54)



(a) pretest



(b) posttest

Figure 4. Student Graphical Responses in the Categorization Dimension: (a) Pretest Data Plotting Without Physical Interpretation; (b) S54 Posttest Response Demonstrating the Correlation Between Linear Graphical Slope and Constant Velocity

Theoretical Comparison: This component challenged students to justify reducing the general kinematic equation $\Delta x = ut + \frac{1}{2}at^2$ to $s = vt$ based on their experimental findings.

Pretest responses were largely restricted to geometric observations. Students frequently noted that "the position-time graph is a straight line" but failed to articulate the theoretical bridge between this geometric observation and the governing equation. Many resorted to circular reasoning (e.g., "it moves with constant velocity, so use $s = vt$ "), without explaining the underlying mathematical justification.

A Partial-proficiency posttest response acknowledged that acceleration must be zero from the graph but could not formally derive the equation reduction. High-proficiency students (e.g., S57) accurately diagnosed the physical constraints, reasoning that because the Arduino data indicated constant velocity, the acceleration (a) must be zero, thus mathematically nullifying the $\frac{1}{2}at^2$ term.

"The experiment found that the object's velocity was constant; therefore, there is no acceleration ($a = 0$). When $a = 0$, the equation $\Delta x = ut + \frac{1}{2}at^2$ reduces to $\Delta x = ut$ or $s = vt$." (S57)

This represents a genuine transition from observation description to deductive theoretical reasoning, extending the constructivist scaffold-

ing principle documented by Hmelo-Silver et al. (2007).

3. Error Analysis: Logical Diagnosis

Within the POE instructional framework, this competency was exercised during the observation phase, when Arduino-generated data deviated from students' initial predictions and required them to diagnose the cause logically.

Uncertainty Analysis: Students were required to evaluate error propagation when presented with a positional uncertainty of ± 0.1 m. Pretest reasoning was typically reductive and vague, such as "The experiment was wrong" or "The sensor made a mistake", without quantitative justification.

Post-intervention, most students (72.3%) were at Partial proficiency, correctly identifying the source of positional uncertainty but not calculating its propagation into velocity. High-proficiency students (e.g., S08) moved beyond generic blame to correctly explain the source of error and calculate the result of velocity uncertainty ($\pm 0.1/\Delta t$).

"A positional uncertainty of ± 0.1 m causes uncertainty in the calculated velocity. Since $v = \Delta s/\Delta t$, where Δs has an uncertainty of ± 0.1 m, the velocity will have an uncertainty of $\pm 0.1/\Delta t$ m/s. For example: If $\Delta t = 1$ second, the velocity uncertainty would be ± 0.1 m/s." (S08)

Hypothesis Formulation: Students were also challenged to hypothesize reasons for a non-linear (curved) graph when a linear relationship was expected.

Pretest explanations were predominantly generalized or tautological (e.g., “there was an error in the experiment”) or attributed errors vaguely to sensor inaccuracy without physical justification (e.g., “It might be caused by the friction, inaccuracies in the Arduino measurements, or the track not being level”), failing to identify underlying sources of error explicitly.

Partial-proficiency posttest responses identified one or two plausible error sources but did not systematically synthesize multiple contributing factors. High-proficiency students moved beyond vague responses to provide scientifically grounded hypotheses, demonstrating the ability to synthesize multiple physical factors to diagnose discrepancies.

“The experiment contained errors from multiple sources, such as: 1) inconsistent friction on the track, 2) inaccuracy of the position sensor, 3) unintentional minor acceleration of the object, and 4) the track setup not being perfectly leveled.” (S42)

This progression directly confirms the theoretical mechanism proposed by Radovanović and Sliško (2013): measurement precision is the critical determinant of cognitive conflict quality in POE instruction, and imprecise manual tools are insufficient to compel this level of analytical diagnosis.

4. Generalization: Extracting Principles From Data

This dimension revealed whether students could identify a linear position-time graph as evidence of constant velocity and connect observed patterns to their initial predictions.

Pattern Recognition: In the pretest, responses were predominantly vague and descriptive (e.g., “position will always increase” or “the graph is linear”), without linking observed patterns to physical significance.

Posttest analysis showed that most students (62.8%) were at Partial proficiency, as they successfully extracted the underlying general principle that a linear position-time (s-t) graph is the physical prerequisite for constant velocity, without explicitly connecting this pattern to their initial predictions. High-proficiency students (2.1%), such as S74, explicitly connected the graphical evidence to prediction validation:

“The position-time graph is a straight line, representing constant velocity. This matches the

initial prediction that the object would move at a constant speed.” (S74)

Validation of Prediction: Students showed marked evolution in how they rationalized inconsistencies between their predictions and the observed data. Lacking any causal reasoning, pretest explanations were frequently ambiguous or tautological (e.g., “An experimental error occurred”).

Partial-proficiency posttest responses acknowledged a discrepancy between prediction and data but attributed it to a single generic cause. High-proficiency students (e.g., S49) demonstrated the ability to synthesize variables to explain deviations from the theoretical ideal:

“If the graph curves upward slightly, it could be due to: 1) Arduino sensor inaccuracies in measuring position; 2) the object having a slight initial acceleration; or 3) inconsistent friction causing velocity fluctuations.” (S49)

5. Specification: Knowledge Application and Innovation

As the highest-order dimension in Marzano’s New Taxonomy, it challenges students to translate kinematic principles beyond the experimental context into functional engineering and real-world design solutions.

Technical Innovation: Students were tasked with engineering solutions to improve the precision of velocity measurement in the original experiment using Arduino technology. They were required to propose at least one innovative design or methodological solution, including a description of its operational principle. Pretest responses offered ambiguous ideas and lacked technical justification (e.g., “Use better sensor to measure more accurately”) without defining the mechanism of improvement.

Post-intervention, Partial-proficiency students (53.2%) proposed a general design improvement using Arduino but did not specify the operational mechanism through which precision would be achieved. High-proficiency students articulated engineering solutions with detailed operational mechanisms. S58, for example, proposed a dual-sensor array to eliminate manual timing errors:

“The design utilizes two ultrasonic sensors interfaced with an Arduino to measure the time interval of an object traversing two points of known distance. The first sensor initiates the timer upon the object’s passage, and the second sensor halts it. Velocity is then calculated using the formula $v = s/t$. This method yields greater accuracy by minimizing errors associated with multiple po-

sition measurements.” (S58)

This proposal demonstrates the successful translation of theoretical motion kinematics into a functional engineering solution.

Real-World Application: The final assessment challenged students to apply constant-velocity concepts to a real-world scenario by designing a residential community speed-monitoring system. This task indicates a successful transition from Generalization (understanding the formula) to Specification (applying that formula to design a functional, novel system).

Pretest proposals provided general intent (e.g., “Create a monitor using Arduino”) but lacked implementation logic concerning how the physics would be applied. In the posttest, S16 successfully extracted the governing principle that velocity calculation requires two fixed spatial measurement points and a precise time interval, and embedded it into a functional community safety design.

“Design a speed monitoring system by installing two infrared sensors 10 meters apart. When a car passes the first sensor, the Arduino starts a timer and stops it when the car passes the second sensor. The speed is calculated as $v = 10 \text{ m/s}$. If the speed exceeds the limit (e.g., 40

km/h), the system triggers an alarm and logs the data and time. This can improve residential safety.” (S16)

These responses demonstrate successful transition from theoretical understanding to practical engineering application. However, Specification retained the highest posttest Limited rate across all five dimensions (38.3%), representing the largest proportion of students for whom the intervention was insufficient to produce genuine knowledge transfer to novel contexts. This finding confirms that translating kinematic principles into functional engineering design is a cognitive demand that exceeds what a 12-hour instructional sequence can fully develop for most students, and identifies Specification as the highest-priority target for extended instructional investment in future implementations.

Arduino-POE Analytical Thinking Development Model

Figure 5 synthesizes the cognitive transformation observed across the full Arduino-POE cycle into the Arduino-POE Analytical Thinking Development Model, which proposes how each POE phase systematically activates distinct analytical thinking dimensions.

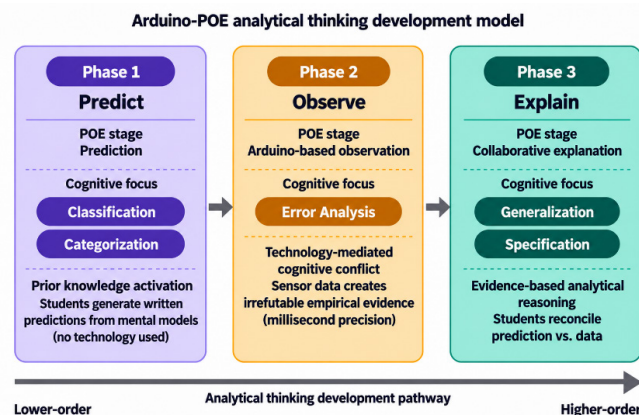


Figure 5. Arduino-POE Analytical Thinking Development Model

The model proposes three sequential cognitive phases aligned with the POE instructional structure. In Phase 1 (Predict), the written prediction task activates students’ existing mental models, creating the conditions for Classification (distinguishing relevant experimental variables from irrelevant ones) and Categorization (organizing prior conceptual knowledge into structured frameworks). Even low-proficiency pretest responses reflect students’ attempts to impose some categorical structure on the problem, confirming that this phase engages these lower-order analytical dimensions from the outset. In Phase 2 (Ob-

serve), the Arduino-based sensor system generates millisecond-precision empirical data that creates unambiguous cognitive conflict between students’ predictions and observed outcomes. This technological precision specifically and forcefully activates Error Analysis, compelling students to logically diagnose the source of discrepancies rather than dismiss them as experimental error, a cognitive demand that imprecise manual tools cannot reliably produce (Radovanović & Sliško, 2013). In Phase 3 (Explain), the collaborative explanation phase requires students to reconcile the prediction-observation gap by constructing gene-

ralized principles from the data (Generalization) and applying those principles to novel engineering and real-world scenarios (Specification).

This model extends the constructivist learning framework of Piaget (1973) and Vygotsky (1978) by specifying which analytical dimensions activate at each instructional phase and by showing empirically that Arduino-generated precision data are the mechanism through which Phase 2 cognitive conflict becomes irrefutable. The collaborative Explanation phase further operationalizes peer-mediated scaffolding consistent with Vygotsky's (1978) Zone of Proximal Development, enabling students to achieve analytical operations beyond their independent capability (Hmelo-Silver et al., 2007; van Uum et al., 2016). Structured scaffolding and teacher guidance have been identified as essential conditions for inquiry-based science education (IBSE) to yield learning gains, a requirement the present model addresses through its researcher-facilitated, phase-specific instructional structure (Strat et al., 2024). Beyond mastering kinematics content, students gained a practical understanding of the nature of science, experiencing firsthand how empirical data drives the evaluation and reconstruction of scientific knowledge (Stadermann & Goedhart, 2021).

The dimension-specific pattern of effect sizes invites a representational interpretation. Bruner's (1966) account of the modes in which knowledge is represented, namely the enactive,

the iconic and the symbolic, offers a lens through which this ordering becomes intelligible. The Arduino-POE sequence supplied most directly a stable and trustworthy iconic representation: a position-time graph whose form could be relied upon exactly because the underlying data were precise. The three dimensions that operate directly upon that representation, Error Analysis, Classification, and Categorization, recorded effect sizes that cluster closely together above the remaining two, consistent with students having been furnished with exactly the resources those operations require. Generalization and Specification, by contrast, require the learner to move from the iconic representation to a symbolic one and then redeploy that symbolic form in an unfamiliar context, a transition that a reliable image does not accomplish by itself. The persistence of Limited proficiency in Specification is therefore not evidence that the intervention failed at its highest level, but an indication that the symbolic and transfer stages demand repeated instructional exposure beyond the 12 hours available here.

Student Satisfaction With Arduino-POE Learning Experience

Table 5 presents the descriptive statistics for student satisfaction across three subscales (learning process quality, innovation characteristics, and perceived learning outcomes) measured on a five-point Likert scale (N = 94).

Table 5. Student Satisfaction With Arduino-POE Instruction (N = 94)

Dimension/Item	M	SD	95% CI	Level
1. Learning Process	4.73	0.53	[4.62, 4.84]	Highest
POE enhances understanding	4.71	0.48	[4.61, 4.81]	Highest
Prediction promotes analysis	4.72	0.51	[4.62, 4.82]	Highest
Observation provides clarity	4.86	0.40	[4.78, 4.94]	Highest
Explanation deepens comprehension	4.71	0.58	[4.59, 4.83]	Highest
Collaborative learning beneficial	4.65	0.69	[4.51, 4.79]	Highest
2. Innovation Quality	4.65	0.57	[4.53, 4.77]	Highest
Timing accuracy	4.41	0.60	[4.29, 4.53]	High
Ease of use	4.66	0.55	[4.55, 4.77]	Highest
Engagement enhancement	4.78	0.53	[4.67, 4.89]	Highest
Data collection efficiency	4.61	0.67	[4.47, 4.75]	Highest
Desire for expanded use	4.79	0.49	[4.69, 4.89]	Highest
3. Perceived Outcomes	4.61	0.62	[4.48, 4.74]	Highest
Conceptual understanding	4.76	0.52	[4.65, 4.87]	Highest
Problem-solving ability	4.61	0.63	[4.48, 4.74]	Highest
Analytical thinking developed	4.79	0.49	[4.69, 4.89]	Highest
Physics confidence	4.70	0.66	[4.57, 4.83]	Highest
Physics attitude	4.18	0.78	[4.02, 4.34]	High
Overall	4.66	0.57	[4.55, 4.77]	Highest

Note. All sub-items (e.g., Timing accuracy, Engagement enhancement) scored ≥ 4.18 .

Students reported particularly high satisfaction with the Observation phase ($M = 4.86$), reflecting that the real-time Arduino feedback made empirical data more credible and conceptually meaningful than traditional textbook examples. Qualitative feedback highlighted that the POE cycle, powered by real-time Arduino digital data, reduced the “boredom” associated with traditional physics lectures and enhanced conceptual understanding. One student noted: “In the past, we just memorized the $v = s/t$ formula without participating in the experiment. With the Arduino, we actually saw the numbers change on the screen as the car moved. It made the theory feel real.” This qualitative testimony aligns with Stadermann and Goedhart’s (2021) argument that direct empirical engagement produces a qualitatively different understanding of the nature of science compared to formula-based passive instruction. The relatively lowest-rated item, though still indicating high satisfaction, addressed general physics attitudes ($M = 4.18$), suggesting that while students valued the specific Arduino-POE experience, it did not necessarily translate to a broader shift in physics enthusiasm, a finding consistent with evidence that affective gains from IBL interventions are domain-specific rather than globally generalized (Öztürk et al., 2022).

These satisfaction findings warrant measured interpretation, since self-reported satisfaction is susceptible to novelty effects and to social desirability bias, particularly in a one-group design (McCambridge et al., 2014). Nevertheless, the convergence between the highest-level satisfaction data in Table 5 and the significant analytical thinking gains in Table 4 strengthens confidence that the Arduino-POE intervention was both cognitively effective and positively received in the resource-constrained rural context, a combination that is essential for scalable, sustainable implementation.

Theoretical and Practical Contributions

The present study makes four contributions that collectively address the gap identified in the Introduction and offer a distinct perspective relative to prior studies in both the Arduino-in-education and POE literature.

First, this study is among the first to systematically integrate Arduino-based sensors with POE instruction and evaluate the impact on Marzano’s (2001) multidimensional analytical thinking as a specifically targeted, five-dimensional cognitive outcome rather than general conceptual gains. Prior studies in the Arduino-in-education literature (Parno et al., 2020; García-

Tudela & Marín-Marín, 2023) and the POE literature (Coştu et al., 2012; Gyeltshen & Wangchuk, 2026) have not reported dimension-specific effect sizes across Marzano’s complete analytical thinking taxonomy. Although Arduino sensors were combined with the POE framework in chemistry education, the assessment was limited to declarative knowledge acquisition. It did not extend to higher-order cognitive dimensions, suggesting that the present study addresses a relatively underexplored position in the literature (Papadimitropoulos et al., 2021).

Second, this study demonstrates that a low-cost open-source tool (23.50 USD, approximately 6% of the commercial equivalent) can generate measurement precision sufficient to support irrefutable cognitive conflict in the POE Observation phase, a theoretical mechanism identified by Radovanović and Sliško (2013) that has received limited empirical testing with Arduino technology in motion kinematics contexts, establishing a preliminary feasibility benchmark for open-source precision instrumentation in resource-constrained physics education.

Third, the Mixed-Methods Analytical Thinking Test (MM-ATT), a custom 30-item validated instrument that operationalizes all five of Marzano’s analytical dimensions through open-ended, scenario-based assessment, represents a methodological contribution not widely reported in the physics education literature. Instruments built on Marzano’s taxonomy have been developed for other science subjects (Sari & Nada, 2022), but none has been reported for motion kinematics with an accompanying qualitative coding frame.

Fourth, the convergent mixed-methods design combining quantitative effect size estimation with qualitative thick description of individual student cognitive transitions offers a level of evidence depth that complements the predominantly single-method quantitative designs found in prior Arduino-in-education and POE studies.

CONCLUSION

This study set out to determine whether embedding an affordable Arduino timing sensor within Predict-Observe-Explain instruction develops analytical thinking among Grade 10 students in resource-constrained rural physics classrooms, and whether students find such instruction acceptable in that setting.

On the first question, the intervention improved analytical thinking across all five of Marzano’s cognitive dimensions, with statisti-

cally significant gains in every dimension. However, the gains were uneven in an interpretable way. Students gained most in the dimensions that operate directly upon the data representation, namely discerning the variables at work and organizing observations into structures linked to physical theory, and least in those requiring them to abstract a governing principle and redeploy it in an unfamiliar context, where a substantial proportion remained below proficiency after instruction. A 12-hour sequence is therefore sufficient to move students from rote recall to evidence-based reasoning about the data in front of them, but not enough for most to transfer those principles to genuinely novel situations. Qualitative analysis of student artifacts confirmed that these gains reflected cognitive restructuring rather than improved recall, documenting a progression from tautological explanation to quantified uncertainty analysis, deductive reduction of the kinematic equation, and functional engineering design.

On the second question, students rated the Arduino-POE learning experience at the highest satisfaction level, with the clarity afforded by the Observation phase rated highest of all the items. This convergence is notable. Students located the value of the experience at precisely the point the cognitive analysis identifies as the mechanism of change: the moment when precise empirical data made the gap between prediction and observation undeniable.

The study therefore offers the Arduino-POE Analytical Thinking Development Model as a replicable framework, built on a device costing approximately 6% of the commercial equivalent. Three limitations warrant acknowledgment. The absence of a control group limits causal inference, the single-researcher implementation constrains ecological validity, and long-term retention of analytical thinking gains remains uninvestigated. Future studies should therefore employ randomized designs with matched control conditions, examine teacher-delivered scalability, and incorporate delayed posttests to assess the durability of cognitive gains.

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