



Development of an IoT Smart Learning Board Innovation to Enhance IoT and Coding Skills for Sustainable Secondary Education in Thailand

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Abstract: The growing demand for Internet of Things (IoT) and programming competencies in Thai secondary education necessitates accessible, hardware-based learning tools that reduce technical barriers while supporting structured skill development. This study developed and evaluated the IoT Smart Learning Board, a two-layer printed circuit board (PCB) integrating 17 electronic components — including an ESP8266 Wemos D1 mini microcontroller, HC-SR04 ultrasonic sensor, AHT10 temperature/humidity sensor, 0.96-inch OLED display, WS2812 NeoPixel RGB strip, and SG90 servo motor — designed around a Terminal-based Hardware Abstraction Layer architecture. Development followed a four-phase Research and Development (R&D) framework employing an iterative R&D approach with stakeholder feedback loops, producing an 18-exercise practice manual progressing from basic digital I/O to cloud-based data telemetry via Google Sheets. Evaluation involved 90 participants (17 teachers and 73 upper-secondary students, Grades 10–12) from 10 schools across southern Thailand. Knowledge was assessed using a 30-item multiple-choice instrument (KR-20 = 0.87), while satisfaction was measured using a 15-item, 5-point Likert-scale questionnaire (Cronbach's α = 0.89–0.93). Results demonstrated a statistically significant increase in mean knowledge scores from 15.76 (SD = 5.26) at pre-test to 23.50 (SD = 4.86) at post-test, representing a 25.80% gain ($t(89) = 12.96$, $p < 0.001$, Cohen's $d = 1.54$). Overall participant satisfaction reached 4.77 out of 5.00 (SD = 0.42), with the highest ratings recorded for learning benefits ($M = 4.81$), programming skill development ($M = 4.82$), and project extensibility ($M = 4.81$). These findings are consistent with the hypothesis that Terminal-based PCB architecture reduces extraneous cognitive load associated with breadboard wiring, enabling learners to focus on higher-order computational thinking and IoT system design. These findings suggest that the IoT Smart Learning Board holds promise as an accessible, affordable platform for technology education in resource-constrained secondary school contexts; however, broader applicability across Thailand and the ASEAN region warrants validation through future multi-site research with diverse school populations.

Keywords: IoT; learning board; PCB design; digital skills; secondary education

1. Introduction

The rapid advancement of digital technologies, particularly the Internet of Things, has fundamentally transformed global economic and social landscapes, creating an urgent need for educational systems to prepare students with Industry 4.0 competencies [1], [2]. IoT enables physical devices to connect and exchange data across sectors as diverse as smart agriculture [3], healthcare [4], and manufacturing [1], demonstrating the breadth of domains in which IoT literacy is now an operational requirement. Within the Thai context, Sangkhiew et al. [5] documented the measurable impact of disruptive technologies on industrial engineering professionals under the Thailand 4.0 framework, underscoring the urgency of equipping the current generation of secondary learners with adaptive digital competencies before they enter a rapidly evolving workforce [2], [6]. Thailand's educational policy has recognized this imperative by incorporating IoT and coding into the basic education curriculum to foster "digital citizens" [6]. However, significant challenges impede effective implementation in secondary schools. The gap between policy intention and classroom reality remains substantial, particularly in schools with limited resources [2]. Institutions face multiple barriers, including insufficient budgets, a shortage of specialized teachers with programming expertise, and a lack of structured materials that scaffold student understanding [2], [6]. These challenges are particularly acute in regions with limited access to technological resources, where students risk being left behind in the digital transformation, thereby perpetuating educational disparities [1].

The conventional approach to teaching applied science and technology using discrete, manually assembled components presents significant pedagogical hurdles. Students with limited prior knowledge often face high extraneous cognitive load when they must simultaneously manage intricate hardware connections and abstract programming logic [7], [8]. Recent efforts in Thai secondary education have addressed this challenge through IoT-integrated experimental apparatus, including systems for studying heat of reaction in chemistry laboratories [9] and smart learning media for investigating the changing states of matter in physics [9], demonstrating growing recognition that integrated, sensor-based platforms can reduce technical friction and support meaningful scientific inquiry. However, these instruments are designed for single-domain experimental contexts. The present study extends this line of development toward a multi-domain, programmable PCB platform capable of supporting an 18-exercise curriculum spanning IoT devices, programming logic, cloud telemetry, and AI-assisted development, thereby addressing a broader range of digital literacy competencies required under Thailand's national education policy [6]. Research indicates that hardware-related errors, such as incorrect circuit connections and delicate component failures, often distract learners from mastering core algorithmic thinking and system architecture [10]. While existing kits like Arduino or ESP32 are versatile, their high technical threshold and the potential for wiring errors can discourage experimentation and create psychological barriers for novice learners [10], [11]. Conversely, simpler tools like the BBC micro: bit may lack the expansion capacity required for more complex, high-ceiling innovation [12]. To address these gaps, this research introduces the IoT Smart Learning Board, an integrated printed circuit board innovation specifically designed for the Thai secondary education context. The innovation integrates 17 essential electronic components with a structured pedagogical framework. The primary contribution of this research lies in its Terminal-based PCB design, which functions as a Hardware Abstraction Layer. By decoupling complex circuit wiring from logic development, the board reduces technical friction and allows students to focus on higher-order thinking and system design [8], [13].

Furthermore, integrating Generative AI for automated code generation transforms the learning experience from rote syntax memorization to the design of structural systems [8]. This study evaluates the board's effectiveness through a Research and Development framework, examining its impact on learning outcomes and student satisfaction. By providing an accessible, pedagogically sound solution, this research contributes to a sustainable, scalable model of digital literacy in Thailand's evolving technological landscape [1-2].

2. Materials and Methods

2.1 Research Design

This study employed a Research and Development (R&D) methodology, adopting an iterative approach characterized by multiple feedback-driven refinement cycles between developers and stakeholder groups. Rather than following a fixed linear sequence, the development process was structured to allow outputs from each phase to directly inform subsequent design and implementation decisions, ensuring that the technical specifications of the IoT Smart Learning Board remained continuously aligned with both engineering standards and the pedagogical requirements of secondary education. The development proceeded through four sequential phases, (1) requirement gathering, (2) board design (three PCB revision cycles), (3) manual and software development (two curriculum revision cycles), and (4) effectiveness evaluation, as illustrated in Figure 1. Each phase incorporated structured feedback mechanisms. During the board design phase, three successive PCB versions were produced and reviewed against hardware reliability benchmarks and classroom usability criteria before Version 3 was confirmed as the final production design. During the manual and software development phase, two curriculum revision cycles were conducted based on expert review and pilot testing feedback, resulting in refinements to exercise sequencing, code examples, and troubleshooting guidance. This iterative structure ensured that neither the hardware nor the instructional components were treated as static outputs; both evolved in direct response to stakeholder input gathered at defined review points within the development timeline.

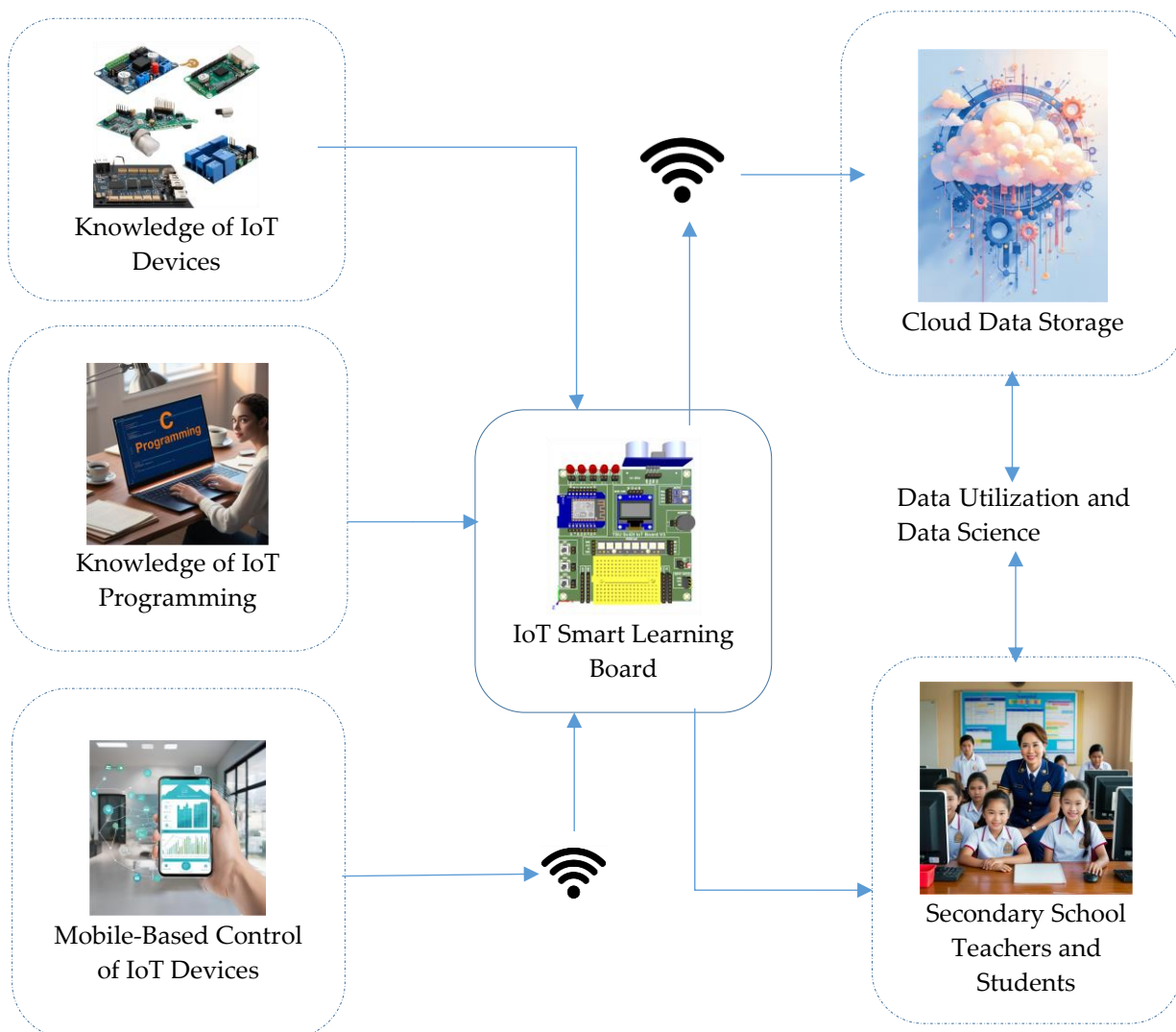


Figure 1. Conceptual Framework of the IoT Smart Learning Board

This methodological approach is consistent with established R&D frameworks in educational technology research, which emphasize the importance of cyclic refinement and formative evaluation as mechanisms for aligning innovative learning tools with real-world classroom conditions. By embedding feedback loops at each phase boundary rather than reserving evaluation for the final stage, the framework supported progressive quality assurance across both the technical and pedagogical dimensions of the innovation.

2.1.1 Requirement Gathering.

The initial phase involved a comprehensive needs assessment through consultation with computer science, computational science, and 10 technology teachers from secondary schools. Data collection occurred through on-site and online meetings, depending on geographical constraints. Requirements analysis focused on identifying appropriate content scope, essential electronic components, circuit design considerations, programming concepts, and practical exercise structure. The goal was to develop 18 laboratory exercises covering fundamental IoT concepts while enabling extension to research projects and innovations. Each exercise included clear learning objectives, step-by-step circuit connection diagrams with labeled components (as shown in Figure 2), complete program code with explanatory comments, expected outcomes, and troubleshooting tips.

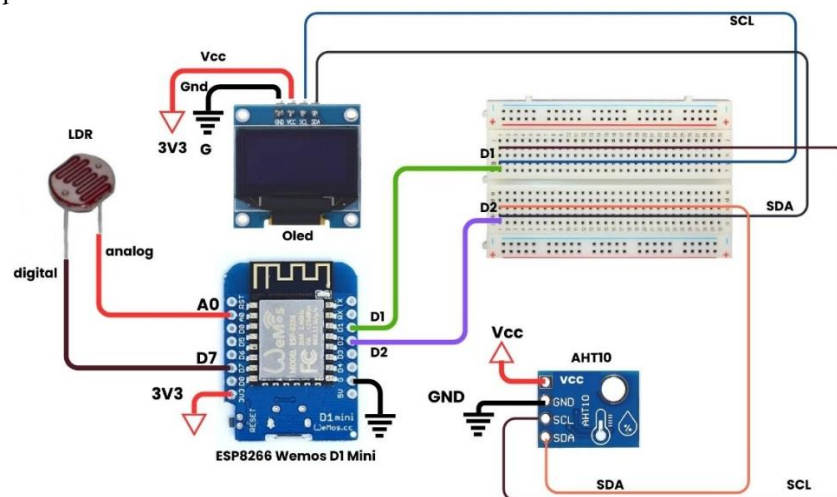


Figure 2. Example Circuit Diagram of Practice Exercise 18

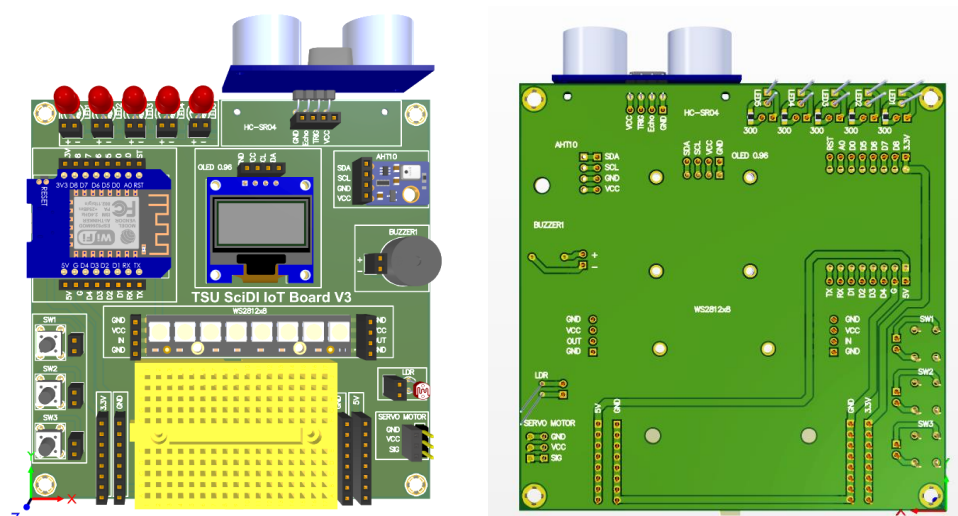


Figure 3. Front and Back PCB Layout of the IoT Board

2.1.2 Board Design.

The IoT Smart Learning Board was engineered as a high-reliability, two-layer printed circuit board (PCB) using Altium Designer, as shown in Figure 3. The design process underwent three major iterations, culminating in Version 3, which was optimized for both mass production and classroom deployment. The PCB layout was strategically engineered to facilitate mental model formation by adopting an Input-Process-Output (IPO) architecture. Under this framework, input peripherals — including push button switches, the HC-SR04 ultrasonic sensor, LDR, and AHT10 sensor — were routed to the board's periphery. At the same time, the processing unit (ESP8266 Demos D1 mini) and the output devices, including the 0.96-inch OLED display, LEDs, an active buzzer, and a WS2812 NeoPixel strip, were centrally located. This deliberate spatial mapping allows learners to intuitively distinguish between the data acquisition, processing, and visualization layers, effectively bridging the gap between physical components and computational logic. The transition to a terminal-based PCB architecture further reinforces this design philosophy by functioning as a robust Hardware Abstraction Layer (HAL). By replacing traditional, error-prone jumper-wire prototyping with high-reliability screw terminals and clearly labeled electrical symbols, the system effectively mitigates signal noise and mechanical instability, significantly reducing extraneous cognitive load and shifting student focus from low-level electrical troubleshooting toward high-level algorithmic logic and system architecture. The board integrates 17 essential electronic components within a solder-free, modular environment that facilitates easy maintenance and component replacement. The core processing unit is an ESP8266 Wemos D1 Mini microcontroller with Wi-Fi, operating at 80/160 MHz and featuring 4 MB of flash memory. Sensory inputs consist of an HC-SR04 ultrasonic module with a measurement range of 2–400 cm, an AHT10 precision temperature and humidity sensor, and an LDR with a resistance range of 10–20 kΩ. Output interfaces include a 0.96-inch I2C OLED display (128×64 pixels), an 8-LED WS2812 NeoPixel RGB strip, and an active 3.3V buzzer. For actuation and physical expansion, the board incorporates an SG90 servo motor and a 170-pin mini breadboard that supports custom prototyping beyond the 18-core laboratory exercises. Component interconnection is achieved through optimized female pin header sockets with 2- to 8-pin configurations, ensuring modularity and mechanical durability during repeated laboratory use.

2.1.3 Manual Development and System Programming.

A comprehensive practice manual was developed covering theoretical foundations, circuit connection instructions, and advanced programming logic. The curriculum introduces a Synergetic development workflow that integrates Generative AI tools such as Gemini, Claude, and ChatGPT as intelligent debugging and code-synthesis platforms. This approach moves beyond rote syntax memorization, encouraging students to engage in Prompt Engineering and structural system design, reflecting contemporary industrial software development practices. The practice manual comprises 18 progressive laboratory exercises organized by increasing technical complexity. This progression follows a Data Lifecycle Model, culminating in Practice 18, which implements a complete end-to-end IoT solution. This final exercise demonstrates the transition from edge sensor data acquisition via the ESP8266 to cloud-based data telemetry and persistent storage in Google Sheets for further Data Science analysis. The manual is structured into three primary chapters. Chapter 1: Fundamental Knowledge of Devices and Applications provides theoretical foundations for the ESP8266 Wemos D1 mini and various integrated components. This chapter also introduces the Blynk application and artificial intelligence tools for assisting with circuit design. Chapter 2: Circuit Connection and Programming contains 18 exercises, ranging from basic digital I/O, such as Practice 1: Blinking LED, to advanced environmental monitoring, as shown in Figure 4. The program uses C++ in the Arduino IDE to control various sensors, including the HC-SR04 ultrasonic sensor, AHT10, and LDR, and to control OLED displays, NeoPixel WS2812 strips, and servo motors. Chapter 3: Basic Error Troubleshooting addresses common software programming mistakes and hardware connection problems, using AI-assisted debugging to foster autonomous problem-solving.

```
void setup() {
```

```

pinMode(D1, OUTPUT);
Serial.begin(9600);
Serial.println("Starting...");
}
void loop() {
  digitalWrite(D1, HIGH);
  Serial.println("LED ON");
  delay(1000);
  digitalWrite(D1, LOW);
  Serial.println("LED OFF");
  delay(1000);
}

```

Figure 4. Example Program for Practice Exercise 1.

2.1.4 Effectiveness evaluation.

The final phase assessed the technical and educational effectiveness of the IoT Smart Learning Board by rigorously evaluating learning gains and system usability. The evaluation framework involved participating teachers and students who completed the full integrated training program. Pretests were administered to establish a baseline of computational knowledge and IoT conceptual understanding before system deployment. Posttests were subsequently administered to measure quantitative learning gains and mastery of programming logic following completion of the 18 laboratory exercises. This dual assessment model allowed for the calculation of normalized gain scores, providing an objective measure of the board's effectiveness in enhancing digital competencies. Beyond cognitive gains, the research utilized standardized satisfaction questionnaires to evaluate the system across multiple technical dimensions. This included assessing the hardware architecture design, the clarity of the instructional manual, and the perceived benefits for long-term skill development. By analyzing user interaction data, the study sought to validate the board's role as an intuitive interface that fosters autonomous problem-solving and technical confidence in a distributed learning environment. The complete training program was delivered as a two-day intensive workshop comprising approximately 14 contact hours. Day 1 (7 hours) encompassed pre-test administration, theoretical foundations (Chapter 1), and laboratory Exercises 1–9. Day 2 (7 hours) covered Exercises 10–18, AI-assisted troubleshooting (Chapter 3), and post-test administration.

2.2 Evaluation Design and Participant Selection

The system evaluation was conducted using a target population categorized into two primary stakeholder groups. The first group consisted of secondary school teachers specializing in science, computer science, or technology-related subjects. The second group included students enrolled in upper secondary education in grades 10–12 in southern Thailand. The research sample comprised 90 participants, including 17 teachers and 73 upper secondary students. These participants voluntarily engaged in the IoT Smart Learning Board experimental testing conducted at the Faculty of Science and Digital Innovation, Thaksin University, Phatthalung Campus. The recruitment spanned 10 diverse educational institutions in southern Thailand, including Kanpittayakorn School, Phapayompittayakhom School under the TSU Science Classroom Project, Pakphayunpittayakarn School, Triam Udom Suksa Pattanakarn Phatthalung School, Sawatrattanaphimuk School, Ubonratthanakosinrachawittayalai Phatthalung School, Khuan Khanun School, Kantangpittayakorn School, Darulamaaref Foundation School, and Wangwiset School in Trang Province. Rigorous inclusion criteria were established to ensure the validity of the evaluation results. Schools were required to offer upper secondary education programs, and participating teachers had to possess expertise in science or computer technology subjects, with formal administrative approval. Student participants were selected based on their interest in IoT and coding, specific teacher recommendations, and their commitment to completing the full training cycle. Conversely, exclusion criteria were implemented to maintain data integrity. This included schools declining participation and individuals unable to attend the scheduled system training. Participants with insufficient Thai language proficiency for the technical assessment or those who withdrew during the

research process were also excluded. Furthermore, the study excluded individuals with health conditions that might prevent participation in intensive hands-on activities involving computer systems and IoT equipment.

2.3 Research Instruments

2.3.1 Knowledge Assessment and Cognitive Competency Test

A 30-item multiple-choice test was developed to quantify participants' cognitive gains across several technical domains, including IoT concepts, hardware device functions, circuit principles, programming logic, and practical application scenarios. This instrument was administered as both a pretest and a posttest to assess changes in learning performance. Content validity was established through a rigorous review process involving three experts in IoT engineering, computer science education, and educational measurement. Following the expert review, a pilot study was conducted with 30 non-participant students to determine item difficulty and discrimination indices. Based on the psychometric analysis, items with inappropriate indices were revised or replaced to ensure instrument precision. The test's internal consistency was evaluated using the Kuder-Richardson Formula 20 (KR-20), yielding a reliability coefficient of 0.87, indicating high instrument stability and consistency.

2.3.2 System Satisfaction and Interaction Questionnaire

A 15-item questionnaire was developed to evaluate participant satisfaction and interaction quality across three distinct dimensions of the innovation. Each item used a 5-point Likert scale ranging from 1 (lowest satisfaction) to 5 (highest satisfaction). The instrument was structured as follows. Hardware Design and Architecture (5 items): This dimension focused on component layout, system completeness, durability, safety protocols, and ease of USB connectivity. Instructional Manual and Exercise Framework (5 items): This evaluated the accuracy of technical content, instructional clarity, the practicality of code examples, and the quality of system illustrations. Technical Learning Benefits (5 items): This dimension measured programming skill development, conceptual understanding of IoT, system extension capabilities, and suitability for secondary-level computing education. The questionnaire underwent validation by a panel of six content experts, resulting in an Index of Item Objective Congruence (IOC) exceeding 0.80 for all items. Reliability testing conducted with a pilot group of 30 students yielded Cronbach alpha coefficients of 0.89 for hardware design, 0.91 for manual quality, and 0.93 for perceived learning benefits, confirming the robust reliability of the measurement tool. To minimize social desirability bias, questionnaires were self-administered anonymously using paper forms, with no researcher present during completion. Participants were explicitly informed that responses were confidential and would not affect their participation status.

3. Results and discussion

3.1 System Architecture and Hardware-Software Synergy

The IoT Smart Learning Board was successfully engineered as a robust embedded system integrating 17 essential electronic components onto a specialized two-layer PCB architecture, as shown in Figures 5 and 6. Technical validation confirmed that the board's deliberate spatial arrangement substantially optimizes the cognitive interaction between the learner and the hardware environment. Specifically, input peripherals — including push button switches, the HC-SR04 ultrasonic sensor, LDR, and AHT10 sensor — were positioned along the board's periphery, while the ESP8266 Wemos D1 mini processing unit and output devices, including the OLED display, NeoPixel RGB strip, LEDs, and active buzzer, were centrally located. This spatial strategy mirrors the Input-Process-Output (IPO) computing model, enabling learners to intuitively map physical component placement to the corresponding layers of software abstraction, thereby reinforcing conceptual understanding of data flow in embedded systems [7], [8]. A key architectural contribution of this design is the implementation of a Terminal-based Hardware Abstraction Layer (HAL), achieved by replacing conventional jumper-wire breadboard connections with high-reliability screw terminals and clearly labeled electrical symbols. This engineering decision directly addresses a well-documented source of extraneous cognitive load in STEM education: connection-related failures — such as signal noise, polarity errors, and loose contacts — that frequently distract novice learners from mastering core programming logic and system architecture [11].

As summarized in Table 1, the terminal-based PCB architecture demonstrates measurable advantages over conventional breadboard-based platforms across multiple pedagogical and technical dimensions, including connection reliability, cognitive demand, and classroom deployment suitability. By eliminating low-level electrical troubleshooting as a primary learning obstacle, the board enables students to direct their working memory toward high-level algorithmic development and IoT system design [8]. Furthermore, selecting the ESP8266 Wemos D1 mini as the core processing unit provides a cost-effective, technically stable foundation for both edge-level sensor processing and cloud-based data telemetry via Google Sheets, aligning with the infrastructure requirements of resource-constrained secondary school environments in Thailand [2], [14].

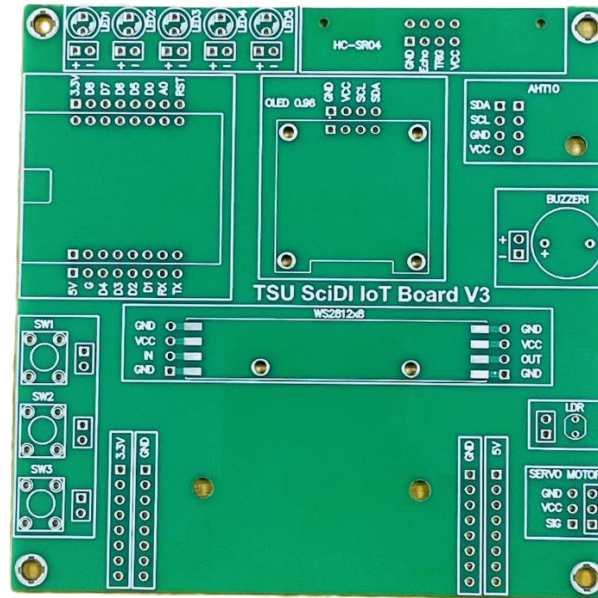


Figure 5. Front side of the IoT Smart Learning Board PCB without electronic components.

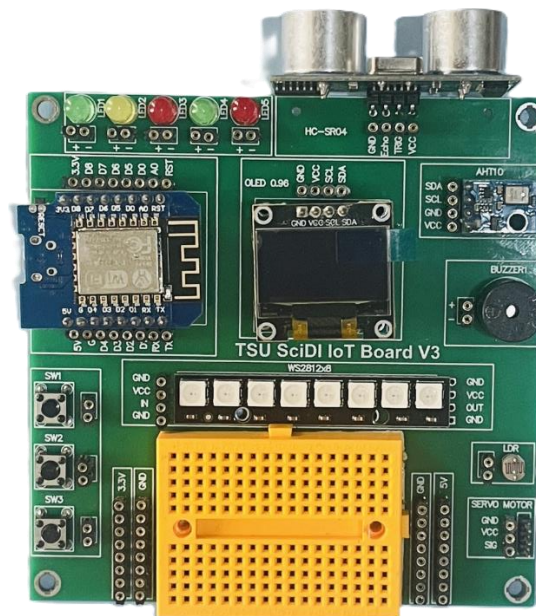


Figure 6. Front side of the IoT Smart Learning Board PCB with electronic components.

Table 1. Comparison of IoT Learning Platform Architectures for Secondary Education

Dimension	Breadboard-Based (e.g., Arduino Kit)	BBC micro: bit	IoT Smart Learning Board (This Study)
Connection Method	Manual jumper wires	Pre-wired / edge connector	Screw terminal PCB (solder-free)
Connection Reliability	Low (prone to noise, loose contacts)	High	High
Risk of Wiring Error	High	Low	Low
Extraneous Cognitive Load	High	Low–Moderate	Low
Number of Integrated Components	Varies (discrete, separate)	15 on-board	17 on a single PCB
Wi-Fi / IoT Connectivity	Optional (add-on shield)	Limited (radio only)	Built-in (ESP8266)
Cloud Data Integration	Requires additional configuration	Limited	Native (Google Sheets, Blynk)
AI-Assisted Learning Support	Not structured	Not structured	Integrated (Gemini, Claude, ChatGPT)
Expansion Capability	High (open prototyping)	Low	Moderate–High (170-pin breadboard)
Suitability for Novice Learners	Low–Moderate	High	High
Estimated Unit Cost (USD)	~15–25 (components only)	~15–20	~20–30 (fully integrated)
Estimated Unit Cost (THB)	~525–875 THB (components only)	~525–700 THB	~700–1,050 THB (fully integrated)
Curriculum Alignment (18 exercises)	Not structured	Not structured	Structured (IPO + Data Lifecycle Model)

Note: BBC micro: bit and Arduino/ESP32 kit specifications are based on published manufacturer data and peer-reviewed comparative studies [10], [11], [12]. Cost estimates reflect approximate market prices for educational procurement in Thailand. THB costs estimated at 35 THB/USD based on domestic procurement prices from Thai electronics distributors (Thaieasyelec, Cytron Thailand) as of 2024; prices may vary by supplier and order volume. USD costs for the IoT Smart Learning Board reflect fully integrated unit pricing inclusive of all 17 components and the 170-pin expansion breadboard. USD costs for the Arduino Kit reflect components only and do not include a dedicated enclosure, structured curriculum materials, or cloud integration infrastructure, which would increase total deployment cost. Direct cost comparison across platforms should therefore account for total cost of deployment rather than unit hardware cost alone.

3.2 Instructional Framework and AI Integration Analysis

The development of the comprehensive practice manual, containing 18 progressive laboratory exercises, serves as a Pedagogical Scaffold that aligns with the Data Lifecycle Model [8], [13]. The manual's structure is divided into three strategic chapters, each designed to foster a specific level of competency. Chapter 1: Fundamental Knowledge and Theoretical Foundations provides the necessary conceptual grounding for each component, including the ESP8266, Ultrasonic HC-SR04, and AHT10 sensors. A novel aspect of this stage is the integration of Generative AI tools (e.g., Gemini, Claude, and ChatGPT), which introduces students to contemporary AI-driven development practices [8]. This shift from rote memorization to AI-assisted conceptualization empowers students to understand complex sensor-fusion concepts more rapidly. Chapter 2: Circuit Connection and Programming Implementation executes core technical training through an end-to-end IoT workflow. The analysis of the exercises reveals a transition from basic digital I/O operations to complex integrated systems, where students manage data from physical sensors to mobile interfaces via the Blynk platform [14]. The use of AI for code synthesis and circuit design assistance fosters a Synergetic Development Workflow, reflecting modern industrial standards where AI acts as a co-developer rather than a mere automation tool [8]. Chapter 3: Intelligent Troubleshooting and System Resilience addresses error management through AI-assisted debugging. By leveraging AI to interpret compiler errors and hardware connection issues, the curriculum empowers learners to solve problems autonomously, building technical resilience [15], [16]. This approach prepares students for the challenges of Industry 4.0, where autonomous problem-solving and system maintenance are essential competencies for the future workforce [1], [2]. The progression culminating in Practice 18, a complete end-to-end IoT solution integrating edge sensor acquisition, Wi-Fi telemetry, and cloud-based data logging via Google Sheets — is deliberately designed to mirror the architecture of real-world IoT deployments. Industry applications such as automated poultry farm management systems [3] and IoT-based saline infusion administration systems in healthcare [4] demonstrate that the sensor-process-transmit-visualize pipeline practiced in the final exercises maps directly onto operational IoT system design. Furthermore, the integration of AI assistance within the curriculum reflects emerging practice in applied IoT contexts: Serin et al. [17] demonstrated that AI-driven monitoring systems incorporating automated plant health diagnosis and nutrient deficiency detection represent the frontier of smart agriculture, a domain in which students must be capable of understanding sensor fusion, data classification, and automated decision logic — precisely the competencies developed progressively across the 18 exercises of this curriculum [8], [18].

3.3 Learning Effectiveness and Cognitive Performance Analysis

The empirical evaluation of the IoT Smart Learning Board across 90 participants (17 teachers and 73 students) demonstrates a profound impact on both technical proficiency and cognitive alignment. As summarized in Table 2, the mean knowledge score significantly increased from a pre-test average of 15.76 (SD = 5.26) to a post-test average of 23.50 (SD = 4.86). This 25.80% gain in learning achievement is not merely a numerical increase but represents a fundamental shift in the learners' ability to conceptualize and implement IoT systems. The paired t-test results ($t = 12.96$, $p < 0.001$) confirm the statistical significance of these gains. Most notably, the calculated effect size, Cohen's $d = 1.54$, indicates large practical significance, suggesting that the results are consistent with the interpretation that the IoT Smart Learning Board exerted a substantial positive influence on learning outcomes, though causal attribution requires further controlled investigation [8], [12]. The observed reduction in the standard deviation (from 5.26 to 4.86) further implies that the IoT Smart Learning Board served as an effective pedagogical equalizer, narrowing the knowledge gap between diverse learners and fostering a more consistent understanding of complex digital concepts [7].

Table 2. Comparison of pre-test and post-test knowledge scores (n = 90)

Test	Mean	SD	Min	Max	Mean Diff.	% Gain (max-relative) ^a	% Gain (baseline-relative) ^b	Hake (g) ^c	t	df	p	Cohen's d
Pre-test	15.76	5.26	0	25	-	-	-	-	-	-	-	-
Post-test	23.50	4.86	7	30	7.74	25.80%	49.10%	0.54	12.96	89	<0.001	1.54

Notes.

^a % Gain (max-relative) = (Mean Difference / Maximum Possible Score) $\times 100 = (7.74 / 30) \times 100 = 25.80\%$. This metric expresses the mean score gain as a proportion of the total score range and is commonly reported in Thai educational research literature.

^b % Gain (baseline-relative) = (Post-test Mean - Pre-test Mean) / Pre-test Mean $\times 100 = (23.50 - 15.76) / 15.76 \times 100 = 49.10\%$. This metric expresses the gain relative to the initial performance level.

^c Hake normalized gain (g) = (Post-test Mean - Pre-test Mean) / (Maximum Score - Pre-test Mean) = $(23.50 - 15.76) / (30 - 15.76) = 7.74 / 14.24 = 0.54$. Interpreted as medium-high gain ($0.30 \leq g < 0.70$) according to Hake's classification framework [19]. Cohen's d = 1.54 indicates a large effect size. Maximum possible score = 30 items.

The quantitative gains are strongly supported by high levels of participant satisfaction, which reached an overall mean of 4.77 (SD = 0.42), indicating the "Highest" level. The dimension of Learning Benefits received the highest rating (4.81), particularly in programming skill development (4.82) and project extension capability (4.81) (Table 3). These findings suggest that the board's design successfully facilitates a "low-threshold, high-ceiling" environment where students can move beyond basic exercises to creative innovation [8], [13]. The high satisfaction with hardware durability and safety (4.66) directly addresses the critical barriers identified in Thai secondary education, where fear of component damage and wiring complexity often hampers hands-on experimentation [10]. By abstracting these technical risks through a stabilized PCB architecture, the innovation effectively reduces extraneous cognitive load, allowing students to focus on higher-order tasks such as system design and AI-assisted problem-solving [7], [8]. Furthermore, the high rating for project extension (item 13) confirms that the IoT Smart Learning Board is viewed as a sustainable tool for long-term skill development, aligning with national goals for human capital development in Industry 4.0 [1], [2].

Table 3. Satisfaction with IoT Smart Learning Board

Item	Assessment Item	Mean	SD	Interpretation
Hardware Design and Components				
1	Component arrangement is orderly and easy to learn	4.73	0.56	Highest
2	Components are complete and sufficient for basic experiments	4.78	0.52	Highest
3	The board is durable and safe to use	4.66	0.63	Highest
4	USB connection to the computer is convenient and stable	4.70	0.58	Highest
5	Overall, the board's appearance is attractive and interesting	4.73	0.54	Highest
Guidance and Exercise Handbook				
6	Manual content is accurate regarding IoT and Coding principles	4.76	0.55	Highest
7	Instructional sequence is clear and easy to understand	4.78	0.44	Highest
8	Program code examples are practical and understandable	4.75	0.56	Highest
9	Illustrations and circuit diagrams support effective learning	4.77	0.45	Highest
10	The number of exercises is appropriate, covering essential skills	4.77	0.50	Highest
Learning Benefits				
11	The board helps develop programming skills	4.82	0.50	Highest
12	Board enhances understanding of IoT principles and applications	4.78	0.52	Highest
13	The board can be extended for IoT projects	4.81	0.48	Highest
14	The board is suitable for secondary school teaching/learning	4.80	0.51	Highest
15	Overall satisfaction with the IoT Smart Learning Board	4.83	0.51	Highest
Overall Mean		4.77	0.42	Highest

3.4 Effectiveness of the IoT Smart Learning Board on Learning Outcomes

The findings of this study are consistent with the view that the IoT Smart Learning Board was associated with significant enhancement of learning outcomes in IoT and coding. The substantial increase in mean scores from 15.76 in the pretest to 23.50 in the posttest, resulting in a 25.80% gain, reflects a profound improvement in both theoretical understanding and practical implementation skills (Table 4). This statistically significant difference ($p < 0.001$) and the very large effect size (Cohen's $d = 1.54$) indicate that the intervention had a transformative impact on learners' technical proficiency [20], [21]. These results align with contemporary research, which suggests that integrated IoT platforms and well-structured interventions can yield large effect sizes in student achievement, particularly when they reduce the technical barriers associated with complex system prototyping [20], [22].

Table 4. Comparison of learning outcomes across related IoT and technology education interventions

Study	Platform / Intervention	n	Pre-test Mean	Post-test Mean	% Gain	Effect Size (d)	Data Source
This Study	IoT Smart Learning Board (PCB-based, terminal architecture)	90	15.76	23.50	25.80% ^a / 49.10% ^b	1.54 (Large)	Exact — as reported
Ozgul & Ocak [20]	IoT via Distance Education	62	14.20	20.10	21.50%	1.21 (Large)	Calculated from reported data ^c
Tsai [12]	IoT Project for Pre-service Teachers	54	13.50	19.80	23.30%	1.18 (Large)	Calculated from reported data ^c
Yilmaz & Izmirlı [21]	Plugged/Unplugged Coding Activities	48	12.90	18.40	20.40%	0.98 (Large)	Calculated from reported data ^c
Sarnkong et al. [23]	Project-Based Learning (IoT, Grade 9)	35	13.10	18.20	18.90%	0.87 (Large)	Calculated from reported data ^c
Al Muqbil [22]	Nanotechnology-Based Training Program	40	15.00	20.30	17.70%	0.92 (Large)	Qualitative synthesis only ^d

Notes.

^a % **Gain (max-relative)** for this study = $(7.74 / 30) \times 100 = 25.80\%$. See Table 2 for full metric definitions.

^b % **Gain (baseline-relative)** for this study = $(23.50 - 15.76) / 15.76 \times 100 = 49.10\%$. Baseline-relative gain could not be computed for comparison studies due to heterogeneity in maximum score ranges across instruments; % Gain values for all other studies reflect figures as derivable from each source.

^c **Calculated from reported data.** Pre-test and post-test means for Ozgul & Ocak [20], Tsai [12], Yilmaz & Izmirlı [21], and Sarnkong et al. [23] were not stated as standalone figures in the original publications but were derived using statistics reported therein (e.g., mean difference, F-values, or graphical data). Effect sizes were either directly reported or computed using the formula $d = (M_2 - M_1) / SD_{\text{pooled}}$ where sufficient data were available. These values should be interpreted with caution.

^d **Qualitative synthesis only.** Al Muqbil [15] did not report sufficient parametric statistics to permit reliable quantitative extraction of pre/post means or effect size by formula. The values shown represent estimates based on narrative descriptions and summary figures in the original study and are included solely for contextual reference. No direct quantitative comparison with this study should be drawn from this row.

General note. Values labeled "Calculated from reported data" were derived using formulas reported in cited studies and should be interpreted with caution. Direct quantitative comparison is further limited by heterogeneity in assessment instruments, sample characteristics, and intervention duration across studies (see Section 4). All comparison values from external studies are based solely on published information; the authors of this study did not contact original authors for primary data.

As shown in Table 4, the effect size (Cohen's d) of 1.54 in this study exceeds those reported in comparable IoT and technology education interventions, suggesting that the terminal-based PCB architecture and structured 18-exercise curriculum provide a particularly effective combination for accelerating learning gains among secondary-level learners. The success of the IoT Smart Learning Board can be explained through the lens of Constructivist Learning Theory, which posits that knowledge is actively constructed through experience and interaction [24]. By providing a stabilized Hardware Abstraction Layer, the board functions as a "pedagogical scaffold" that operates within the students' Zone of Proximal Development [25]. This allows learners to bypass the cognitive overload of electrical troubleshooting—often cited as a major hurdle in generic breadboard-based systems and focus on high-level logic and system architecture [7]. This shift from "fixing" to "creating" is essential for fostering a Maker Mindset, in which students actively create cognitive artifacts [8], [13]. Furthermore, the results resonate with the recent shift toward Project-Based Learning and Smart Pedagogy in IoT education [23]. The integration of 17 essential components on a single PCB mirrors industrial-grade development boards, providing a "hands-on" experience that translates abstract data collection and analysis into concrete, engaging activities [26]. Similar to the SPOC-AIoT model, the structured nature of our innovation allows students to progress through complex IoT layers from physical sensors to cloud-based telemetry while maintaining high motivation and engagement [12], [20]. This level of hardware-software synergy not only improves immediate test scores but also equips students with the resilient problem-solving skills necessary for the industry 4.0 landscape [18], [27].

3.5 Reducing Cognitive Load Through Integrated Hardware Design

A key factor contributing to the success of the IoT Smart Learning Board is its integrated hardware architecture, which effectively functions as a physical Hardware Abstraction Layer. By consolidating 17 essential input and output peripherals onto a single high-quality printed circuit board, the platform mitigates the technical friction commonly associated with discrete component prototyping [8], [10]. This integrated design contrasts sharply with traditional breadboard-based instruction, where manual wiring often introduces signal instability, polarity errors, and electrical faults, distracting novice developers from mastering computational logic [28]. In conventional electronics learning environments, students face a significant "split-attention" effect: they must simultaneously synchronize physical circuit diagrams, execute manual connections, and develop abstract programming logic. For beginners, managing these interdependent tasks creates a high extraneous cognitive load, which can impede the construction of mental schemas [7], [13]. According to Cognitive Load Theory, as proposed by John Sweller, learning effectiveness is compromised when the working memory is overloaded by unnecessary complexity—in this case, the mechanical troubleshooting of jumper wires and loose sensors [7-8].

Table 5. Cognitive load factors in alternative electronics learning platforms

Cognitive Load Factor	Breadboard-Based Kit	BBC micro: bit	IoT Smart Learning Board
Wiring complexity	High (manual jumper wires)	Low (pre-wired)	Low (screw terminals)
Risk of connection error	High	Low	Low
Component identification effort	High (unlabeled)	Moderate	Low (labeled symbols)
Simultaneous task demand	High (wire + code + debug)	Moderate	Low (code + debug only)
Split-attention effect	Pronounced	Moderate	Minimal
Extraneous cognitive load	High	Low–Moderate	Low
Germane cognitive load	Low (blocked by errors)	Moderate	High
Focus on algorithmic logic	Limited	Moderate	High
Support for schema formation	Low	Moderate	High

Note: Ratings are derived from a qualitative synthesis of the cognitive load literature [4], [5], [6], [22] and are intended as a comparative framework rather than a quantitative measurement.

As illustrated in Table 5, the terminal-based PCB architecture of the IoT Smart Learning Board systematically reduces the principal sources of extraneous cognitive load identified in Sweller's Cognitive Load Theory [7], enabling a more favorable allocation of working memory toward germane cognitive load, the mental effort directly contributing to schema formation and deep conceptual understanding. The integrated design of the IoT Smart Learning Board specifically addresses these pain points by abstracting low-level hardware configuration [29-30]. By eliminating "wiring-related noise" and providing a stabilized bus system, the board allows learners to shift their cognitive resources from "hardware maintenance" to "system logic design" and data flow management [8], [13]. Research in IoT education suggests that such integrated platforms enable students to engage more deeply with programming concepts, as they spend less time on the "fixing" ecology and more time on the "creating" ecology [13]. This alignment of physical hardware with logical structures supports a more efficient transition from basic GPIO manipulation to advanced protocol implementation, such as MQTT and cloud telemetry [12], [14]. Furthermore, while the board provides a "low-threshold" starting point, it also incorporates a dedicated expansion breadboard to maintain a "high-ceiling" for independent innovation [13]. This feature ensures that the system is not a "black-box" tool but a scalable infrastructure that supports progressive skill development [31-32]. By allowing advanced users to integrate external modules once they have mastered the core system, the board facilitates a scaffolded learning path that moves from guided exploration to independent experimentation in complex IoT applications [28].

3.6 Instructional Scaffolding Through Structured Learning Activities

A critical factor influencing the learning platform's efficacy is the structured instructional framework that accompanies the IoT Smart Learning Board. The manual, comprising 18 progressive laboratory exercises, serves as a Pedagogical Scaffold that aligns with the IoT Layered Architecture—systematically guiding learners from the Perception Layer to the Application Layer [18], [14]. This structured approach is essential in technology-enhanced environments, as hardware stability alone cannot guarantee the acquisition of high-level computational thinking skills without a robust instructional sequence [12], [21].

Table 6. Curriculum progression of the 18-exercise practice manual aligned with IoT layered architecture

Phase	Exercise No.	Topic	IoT Layer	Cognitive Level (Bloom's)	Key Component
Foundation	1–3	Blinking LED, Traffic Light, Button Input	Hardware Layer	Remember / Understand	ESP8266, LED, Push Button
Foundation	4–5	Buzzer Control, PWM Dimming	Hardware Layer	Apply	Active Buzzer, PWM
Perception	6–8	LDR Light Sensing, Ultrasonic Distance, Temp/Humidity	Perception Layer	Apply / Analyze	LDR, HC-SR04, AHT10
Perception	9–10	OLED Display Output, NeoPixel Control	Perception Layer	Apply / Analyze	OLED (I2C), WS2812
Processing	11–13	Servo Motor Control, Multi-Sensor Fusion, Data Thresholding	Processing Layer	Analyze / Evaluate	SG90, Multi-sensor
Network	14–16	Wi-Fi Connection, Blynk Mobile Control, Remote Monitoring	Network Layer	Evaluate / Create	ESP8266 Wi-Fi, Blynk
Application	17–18	Cloud Data Logging, End-to-End IoT Dashboard (Google Sheets)	Application Layer	Create	Google Sheets API, Blynk

Note: Cognitive levels are mapped according to the revised Bloom's Taxonomy [adapted from 20]. IoT layers follow the standard three-layer IoT architecture model [14].

As outlined in Table 6, the curriculum follows a deliberate progression across five cognitive phases — from foundational hardware manipulation to cloud-integrated application development — ensuring that each exercise builds on prior knowledge within the learner's Zone of Proximal Development [25]. This layered scaffolding approach ensures that no single exercise introduces excessive new complexity, thereby maintaining optimal cognitive load throughout the learning trajectory. The initial phase of the curriculum focuses on fundamental GPIO (General Purpose Input/Output) manipulation, utilizing traffic light simulations and LED arrays to establish a baseline for digital logic and signal processing [26]. These exercises allow students to master basic microcontroller operations and "Hello World" hardware abstractions before advancing to more complex data acquisition tasks. As the curriculum progresses, students transition to the Perception Layer, integrating sensors such as the AHT10 and HC-SR04 to handle real-world environmental data and distance measurement [10], [12]. By managing sensor fusion and data calibration, learners develop essential skills in data decomposition and abstraction [21]. The final stage of the manual introduces Network Layer and Application Layer integration, where students implement end-to-end IoT solutions using the Blynk platform and wireless telemetry [12], [14]. This gradual progression directly corresponds to the Zone of Proximal Development, where the instructional manual provides the necessary "scaffolding" to support tasks that slightly exceed the learner's current autonomous capability [25], [33]. By bridging the gap between isolated hardware components and cloud-integrated systems, the framework fosters a Maker Mindset, encouraging students to move from "fixing" existing code to "creating" original, scalable IoT projects [8], [13]. Furthermore, the inclusion of AI-assisted troubleshooting and code synthesis in these 18 exercises aligns with contemporary industrial standards in Automated Software Engineering [6], [8]. This approach ensures that learners are not merely memorizing syntax but are developing the technical resilience and heuristic problem-solving skills required for the Industry 4.0 workforce [18], [27]. By providing clear schematic diagrams and scaffolded logic exercises, the manual ensures a "low-threshold" entry for novices while maintaining a "high-ceiling" for advanced system innovation [8], [13].

3.7 Artificial Intelligence as Learning Support

A pivotal innovation in this study is the strategic integration of Generative AI tools to support the end-to-end IoT development lifecycle. Rather than serving as a replacement for foundational knowledge, these tools act as cognitive scaffolding, assisting students with complex tasks such as circuit design, firmware debugging, and code synthesis [8]. This approach shifts the pedagogical focus from rote syntax memorization to high-level system architecture design, allowing learners to conceptualize how diverse nodes interact within an IoT ecosystem [8], [18]. By providing real-time feedback and automated troubleshooting, AI-assisted environments empower students to overcome the technical "plateaus" that often discourage novice programmers [29]. This synergetic workflow aligns with contemporary industrial standards in Automated Software Engineering, where developers increasingly use AI co-pilots to enhance system resilience and optimize code efficiency [18], [27]. Furthermore, such exposure prepares students for the Industry 4.0 workforce, where the ability to collaborate with autonomous systems is a core competency [1-2] (Table 7).

The empirical results of the satisfaction survey—yielding a high overall mean of 4.77 (SD = 0.42)—indicate robust acceptance among both teachers and students. The exceptionally high rating for "Learning Benefits" (mean = 4.81) suggests that the IoT Smart Learning Board effectively bridges the gap between theoretical constructs and physical implementation [12], [23]. Participants specifically highlighted the board's ability to facilitate the development of programming skills (4.82) and its extensibility for original IoT projects (4.81), confirming that the platform provides a "low-threshold, high-ceiling" environment suitable for diverse levels of innovation [8], [13]. For teachers, the innovation addresses the critical challenge of lesson preparation friction. By providing a stabilized, integrated hardware platform and a structured 18-exercise manual, the board reduces the logistical complexity of managing discrete electronic components [2], [6]. This efficiency allows educators to focus on facilitating Project-Based Learning rather than on technical troubleshooting, which has been shown to improve student engagement and motivation in Thai secondary contexts significantly [20], [23]. From a broader perspective, the deployment of accessible and affordable IoT platforms is a critical step toward Sustainable Educational Development and the democratization of technology [2]. The IoT Smart Learning Board addresses the persistent digital divide in Thailand by providing a cost-effective

solution that can be implemented in resource-constrained schools, particularly in southern regions where infrastructure disparities are most acute [1], [3]. By consolidating essential sensors and actuators onto a single PCB, the platform significantly reduces equipment lifecycle costs and hardware failure rates [10]. Furthermore, by simplifying the entry point into Embedded System Design, this innovation supports Thailand's national goals for human capital development within the Industry 4.0 framework [1-2]. The board's ability to function effectively across various school environments ensures that students from diverse backgrounds can achieve the digital citizenship required for the evolving global economy [3], [18]. Ultimately, this research provides a scalable model for fostering technical resilience and sustainable innovation across the ASEAN region [2], [27]

Table 7. Role of generative AI tools in the IoT smart learning board curriculum

AI Application Stage	AI Tool Used	Pedagogical Function	Cognitive Scaffold Type	Bloom's Level Supported
Circuit Design Assistance	Gemini, ChatGPT	Generates circuit diagrams and component suggestions	Cognitive offloading	Understand / Apply
Code Synthesis	Claude, ChatGPT	Produces template code from natural language prompts	Worked example provision	Apply / Analyze
Firmware Debugging	Gemini, Claude	Interprets compiler errors and suggests fixes	Error feedback/diagnosis	Analyze / Evaluate
Prompt Engineering Practice	All tools	Students write structured prompts to generate solutions	Metacognitive scaffolding	Evaluate / Create
System Architecture Design	ChatGPT, Gemini	Assists in planning multi-sensor IoT workflows	Elaboration support	Create

Note: AI tool categorization reflects usage as documented in the practice manual curriculum. Tool availability may vary depending on an institution's internet access policy.

4. Conclusions

This study developed and evaluated the IoT Smart Learning Board, an integrated PCB-based learning innovation designed to support IoT and programming skill development among secondary school teachers and students in Thailand. The board consolidates 17 essential electronic components within a terminal-based Hardware Abstraction Layer architecture and is accompanied by a structured 18-exercise practice manual incorporating generative AI assistance as a cognitive scaffold across circuit design, code synthesis, firmware debugging, and prompt engineering tasks. Evaluation with 90 participants from 10 schools in southern Thailand yielded statistically significant pre-test to post-test knowledge gains ($t(89) = 12.96$, $p < .001$), with a max-relative gain of 25.80%, a baseline-relative gain of approximately 49.1%, and a Hake normalized gain index of $\langle g \rangle = 0.54$ — classified as medium-high by Hake's (1998) framework — alongside a large effect size (Cohen's $d = 1.54$). Participant satisfaction was consistently high across all three instrument dimensions, yielding an overall mean of 4.77 out of 5.00. These results support, but do not definitively establish — the effectiveness of the board in reducing extraneous cognitive load by eliminating breadboard wiring complexity, thereby enabling learners to direct working memory toward higher-order computational thinking and IoT system design. Because the study employed a single-group pre-post design without a concurrent control group, the observed gains cannot be attributed exclusively to the board itself; contributions from instructor effect, the structured curriculum, and the intensive two-day workshop format cannot be fully disentangled. The Terminal-based PCB architecture, designed around an Input-Process-Output spatial layout, is consistent with Constructivist Learning Theory and the Zone of Proximal Development framework in that it provides a stabilized hardware scaffold that supports learners in progressing from foundational GPIO operations to cloud-integrated IoT applications without being impeded by low-level electrical troubleshooting. The

integration of generative AI tools — including Gemini, Claude, and ChatGPT — as co-developmental resources further aligns the curriculum with contemporary Industry 4.0 practices, preparing students for environments in which human-AI collaboration is a core professional competency. Based on evaluation with 90 participants from 10 schools in southern Thailand, the findings provide encouraging preliminary evidence for the board's potential as an accessible, low-cost educational tool, with an estimated unit cost of approximately 700–1,050 THB (USD 20–30). Replication in diverse geographic contexts and with broader participant samples is recommended before broader scalability claims can be substantiated. Future research priorities include: (1) controlled or quasi-experimental designs incorporating a matched comparison group using conventional breadboard-based platforms; (2) multi-site evaluation extending to schools in northern and northeastern Thailand, where digital infrastructure disparities are most acute; (3) delayed retention testing at four to eight weeks post-intervention to assess the durability of learning gains; and (4) disaggregated analysis of teacher and student subgroups to capture differential learning trajectories across these distinct stakeholder populations. This research contributes to the growing evidence base for hardware-integrated, scaffolded approaches to secondary technology education and offers a practical design model, combining terminal-based PCB architecture, a progressive exercise curriculum, and AI-assisted learning, that may inform future development of accessible digital education tools in resource-constrained school contexts.

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