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Process Gains, Difficulty Restructuring, and Dependency Risks in AI-Assisted Hardware-Driven Design Education: A Crossover Experimental Study

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Abstract

Generative artificial intelligence (AI) has demonstrated significant potential in education, yet empirical research on its application in "hardware-driven" interdisciplinary design courses remains scarce. This study employed a randomized crossover experimental design in an IoT Hardware and Design Innovation course at Hunan University. Twelve industrial design undergraduates with no prior IoT background alternated between AI-assisted (ChatGPT-4o) and traditional learning resource conditions across six short-cycle tasks. The crossover design enabled each participant to serve as both experimental and control subjects, yielding 72 observation-level data points. Grounded in Cognitive Load Theory, the study examined three dimensions: process efficacy, difficulty structure, and switching adaptation costs. Results indicated that AI significantly improved perceived task completion efficiency, self-reported goal attainment, and learning experience, yet self-assessed knowledge transfer did not differ significantly between conditions. AI reduced the total number of reported difficulties but altered the difficulty-type distribution: resource-retrieval difficulties decreased while information-verification difficulties increased—a phenomenon we term "difficulty restructuring". Furthermore, switching from AI back to traditional resources incurred significantly higher adaptation costs than the reverse transition, revealing emerging dependency risks. These findings suggest that generative AI may function more as a "difficulty restructurer" than a "difficulty eliminator" in hardware-driven design education, providing exploratory empirical evidence for incorporating verification literacy into future course design and calling for calibrated scaffold fading that may help mitigate emerging dependency risks.

Keywords: generative artificial intelligence; design education; internet of things; cognitive load theory; crossover design; difficulty restructuring; interdisciplinary education

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1. Introduction

As one of the benchmarks in design education, the MIT Media Lab is renowned for its interdisciplinary, innovation-driven educational model, particularly in bridging design, technology, and art. Its innovative educational philosophy has influenced many design education platforms worldwide, including Aalto University's Design Factory in Finland and Olin College of Engineering in the United States. The MIT Media Lab's former motto was "Demo or Die", emphasizing that design students must possess sufficient creativity and hands-on ability to rapidly prototype and iterate. The current requirement is even more

pragmatic, having evolved to "Deploy or Die", which emphasizes that design students must not only rapidly build prototypes but also quickly transform them into truly deployable products [1]. However, for the vast majority of design-background students, accomplishing this goal without collaborating with technically proficient engineering students is extremely difficult. The traditional curriculum for industrial design majors typically emphasizes core courses such as design history, design methodology, and human factors engineering [2]; compared to students in electronic engineering or computer science, design students lack systematic foundations in electronic engineering and programming. Research indicates that approximately two-thirds of design students encounter serious difficulties when learning electronics and programming [3]. From the perspective of Cognitive Load Theory (CLT), when learning content possesses high "element interactivity" and learners have insufficient prior knowledge, intrinsic cognitive load escalates sharply [4], often resulting in frustration, anxiety, and disengagement. The interdisciplinary knowledge gap constitutes not merely an inconvenience but a structural barrier to design innovation in an increasingly connected world.

In recent years, the most profoundly and broadly influential new technology has been the rapid development of AI technology, represented by generative artificial intelligence. As an innovative tool in the educational domain, AI has demonstrated unprecedented potential. Generative AI conversational tools, such as ChatGPT, have already achieved significant application outcomes in teaching across multiple disciplinary fields. AI can interact with students in real-time through natural language processing, providing learners with instant feedback, personalized guidance, and suggestions in practice, assisting students in overcoming difficulties during the learning process, stimulating creative thinking, and enhancing learning outcomes. Moreover, generative AI chatbots possess distinct interdisciplinary characteristics that can be extended to various disciplinary domains [5]. Specifically for technology-intensive courses such as "IoT Hardware and Design Innovation", we anticipate that the application of generative AI could effectively supplement students' knowledge gaps in programming, hardware design, and other areas, helping them more rapidly master complex concepts and skills, thereby reducing students' cognitive load and psychological burden, alleviating learning anxiety, and enhancing design students' confidence and competence in interdisciplinary learning.

However, despite the preliminary achievements of generative AI educational applications in some fields, systematic empirical research integrating hardware technology into design curricula remains limited. Much of the existing literature consists of review papers that lack robust empirical evidence directly demonstrating AI's ability to improve design teaching quality [6]. Although a few empirical studies have explored how AI tools assist student learning and enhance learning outcomes, most are narrow in scope—primarily focused on general education contexts and consisting of small-scale case studies or questionnaire surveys that rarely investigate how AI supports design students' hardware technology learning processes. Accordingly, this study attempts to explore the effects of generative AI on learning processes and learning outcomes in a hardware-driven design course through an empirical experiment.

Over the past three years, our research team has been exploring the possibilities of combining design teaching systems with hardware technology through the "IoT Hardware and Design Innovation" course at the School of Design, Hunan University. This course was selected as the research platform for two primary reasons. First, future design practices are inevitably moving toward digitalization, interconnection, and intelligence, and IoT technology serves as the foundational infrastructure for innovative applications in industrial design, such as smart products, smart homes, and smart cities [7]. Open-source hardware and hardware interaction courses offered by major design schools worldwide are, in practice,

closely intertwined with IoT hardware technology. IoT technology has already permeated every aspect of daily life and work, driving the realization of human-centered design concepts, and even gradually transitioning toward object-centered approaches, inspiring posthumanist design thinking [8]. Therefore, the widespread application of IoT design innovation courses has become an indispensable component of modern design education.

Second, "IoT Hardware and Design Innovation" is an interdisciplinary course that integrates computer technology, electronic engineering, and creative design. In this process, if design-background students can master the ability to construct simple IoT systems through this course, they can overcome the technical and psychological barriers—such as weak programming skills and limited hardware knowledge—that are inherent in traditional design education. This not only helps them master foundational technologies but also inspires their ability to incorporate engineering technology into design. Furthermore, if students can understand the collaborative functioning and interconnection of various functional modules within IoT systems and comprehensively grasp the basic framework of IoT architecture, they will be better positioned to promote the seamless integration of technology and design, thereby advancing the realization of innovative interdisciplinary design.

We refer to this pedagogical context as hardware-driven interdisciplinary design education—a setting in which industrial design students engage in physical computing practices [9,10] as core curricular activities. Students systematically participate in microcontroller programming, sensor integration, and IoT system prototyping as part of a technology-driven design process [11]. Unlike conventional design studio curricula that foreground form, aesthetics, or user research, this context requires students to simultaneously navigate hardware debugging, software logic, data communication, and design integration, rendering the learning environment distinctly interdisciplinary and technically intensive.

This study provides preliminary evidence for this under-researched educational context by examining the effects of generative AI on the learning process as industrial design students undertake IoT hardware engineering tasks. Employing a randomized crossover design—in which each participant alternated between AI-assisted and traditional resource conditions across six tasks—the study leverages repeated within-subject measures to control for individual differences. Grounded in Cognitive Load Theory (CLT), the study addresses five aspects: whether AI enhances process-level efficacy, whether it facilitates knowledge transfer, whether it improves learning experience, whether it changes the difficulties encountered during learning, and whether the adaptation costs of switching between AI and non-AI learning conditions are symmetric. The exploratory contributions of this study are threefold. First, it provides crossover-experimental evidence in the under-studied context of hardware-driven design education. Second, it examines whether AI's impact on learning difficulties extends beyond simple "reduction or increase", exploring potential structural shifts in difficulty type distributions. Third, through adaptation cost data from condition switching within the crossover design, it offers preliminary empirical reference for discussions on dependency in AI-assisted learning.

2. Literature Review

2.1. Application of Generative AI in Design Education

AI has been progressively penetrating the educational domain year by year, transitioning from general-purpose text generation tools to highly specialized virtual tutors. Generative AI, represented by ChatGPT, is based on natural language processing technology and can handle multi-turn interactions while providing students with highly personalized learning experiences [12]. For instance, it can generate targeted explanations, examples, and exercises based on students' specific questions and learning progress, thereby helping students overcome knowledge gaps and strengthen understanding. Furthermore, by

providing instant feedback, ChatGPT can help students correct errors in a timely manner, avoiding biases in knowledge accumulation, and improving students' knowledge retention and application ability within a short period [13]. The effectiveness of generative AI as a teaching assistant tool has been widely recognized in general education and language learning, significantly transforming traditional learning models [14,15]. In 2025, over 70% of students worldwide used ChatGPT for learning, indicating that ChatGPT has become a core component of students' daily learning tools [16].

In the field of design education, AI is reshaping creative design processes and teaching practices. Generative AI tools (such as ChatGPT, Midjourney, and DALL-E) help students generate ideas, explore concepts, and create visual prototypes by automatically generating text, images, and three-dimensional models [17]. Integrating AI tools into design education has been shown to expand design students' creative potential and enhance the originality and quality of their design proposals [6]. Simultaneously, students can utilize AI tools to rapidly validate concepts and explore stylistic variations, accelerating design iterations and thereby improving learning efficiency [18]. Research has further found that introducing GenAI into design courses enables students to engage in self-paced, autonomous interaction and adaptive learning, enhancing their engagement and learning motivation [19]. Additionally, GenAI has the potential to optimize design workflows and automate assessment, reducing the cognitive load on design students and allowing them to focus on creativity and problem-solving [20].

However, the aforementioned research primarily focuses on the pedagogical applications of AI in design creativity and visual expression, while research on AI-assisted hardware technology learning for design students remains relatively scarce. In the field of engineering education, AI tools have been demonstrated to assist engineering students with code debugging and algorithm optimization, improving their performance in code quality and logical completeness [21]. GenAI in interdisciplinary higher education can help students integrate knowledge and skills across domains, facilitating knowledge transfer [22]. Nonetheless, research on AI for integrating design thinking and technology remains in its infancy, particularly in technology-intensive courses involving hardware-driven and sensor-integrated curricula, where the intervention effects of AI among design students still lack systematic research and evaluation.

2.2. Challenges Faced by Industrial Design Students in IoT Technology Learning

The core of Internet of Things (IoT) technology lies in connecting heterogeneous devices such as sensors, actuators, and gateways through networks, enabling data collection, transmission, and processing [23]. The technical architecture of IoT systems is highly complex, primarily manifested across three following dimensions.

Device diversity: IoT devices may employ different hardware platforms (e.g., ARM, x86), operating systems (e.g., Linux, RTOS, embedded systems), and communication technologies (e.g., Wi-Fi, Bluetooth, Zigbee, LoRa), requiring developers to possess cross-platform development capabilities.

Communication protocol complexity: Inter-device communication in IoT requires adaptation to multiple protocols such as MQTT, CoAP, and HTTP, with developers needing to select appropriate solutions based on application scenarios and ensure compatibility.

Data processing and management difficulty: IoT systems must handle large volumes of real-time data streams and historical data for collection, storage, and analysis. In scenarios combining edge computing and cloud computing, data synchronization and consistency management are particularly complex, imposing higher demands on technical capability.

Courses developed based on IoT technology in higher education inherently possess interdisciplinary and strong application-oriented characteristics, spanning electronic

engineering, computer science, and communication technology, among other fields. Learners must understand and master multidisciplinary knowledge to complete the technical implementation pathway from hardware design, software development, network communication, to data processing [24]. The continuous updating of standards and protocols in the IoT domain also increases the learning burden. Moreover, IoT technology learning requires extensive hands-on practice (e.g., hardware assembly, programming and debugging), placing high demands on practical skills [25].

With the rapid development and proliferation of smart products, IoT technology has gradually become one of the technical categories that industrial design students need to master [26], yet such technology-driven design courses are extremely challenging for design students. The traditional curriculum for industrial design majors typically emphasizes core courses such as design history, design methodology, and human factors engineering [2]. Compared to students in electronic engineering or computer science, design students lack systematic foundations in electronic engineering and programming. This interdisciplinary knowledge gap creates a steep learning curve for design students. Research indicates that approximately two-thirds of design students encounter serious difficulties when learning electronic knowledge and programming, subsequently making it difficult for them to meet the basic technical requirements of electronic product design [3]. From the perspective of Cognitive Load Theory, when learning content possesses high "element interactivity" (i.e., requiring simultaneous processing of multiple interrelated elements) and learners have insufficient prior knowledge, high cognitive load and learning difficulty are imposed on learners [4], which may further undermine students' confidence.

This technological divide not only increases the learning burden but may also limit students' innovative capacity in IoT product design. For instance, students may struggle to translate design concepts into functional IoT prototypes because during the prototyping and debugging phase, students often need to locate faults across hardware wiring, code, networks, and servers, with some problems being unexplainable and untraceable solely from the code level [27]. Such frequent failure and "implementation gaps" may generate frustration and anxiety among design students during the learning process, making it more difficult for them to master IoT-related knowledge and skills. Research shows that programming anxiety significantly reduces learners' engagement, performance levels, and knowledge retention, and may lead to lower course completion rates [28]; when learning materials are overly complex, learners are more inclined to discontinue learning, exhibiting high dropout rates [29].

To address these challenges, design students need more pedagogical support to cope with the complexity of IoT technology (e.g., dedicated IoT prototyping toolkits, IoT product examples/templates, AI-assisted teaching scaffolds), to lower the entry barrier and support their translation of design concepts into functional prototypes [26]. However, existing interdisciplinary design education research still lacks structured teaching frameworks tailored to the characteristics of design students. Therefore, this study introduces generative AI as a cognitive support tool, through systematic pedagogical intervention design, to explore its potential in lowering the barriers to hardware technology learning, enhancing learning outcomes, and optimizing learning experiences. Specifically, the decision to position generative AI as a cognitive support tool draws on the theoretical tradition of instructional scaffolding. Wood et al. [30] conceptualized scaffolding as a process in which a tutor enables a learner to accomplish tasks beyond their independent capability. The tutor controls task elements that initially exceed the learner's ability and dynamically adjusts the level of intervention as the learner progresses. In the present context, generative AI assumes this role by delivering contingent, on-demand explanations tailored to each learner's queries, while the crossover design enables systematic observation of what occurs

when this scaffold is alternately provided and withdrawn. This theoretical lens underpins the study's core research questions: whether AI-as-scaffold enhances process-level efficacy (RQ1) and whether the adaptation costs of providing versus withdrawing this scaffold are symmetric (RQ5).

2.3. Potential Risks and Challenges of Generative AI in Teaching

Despite generative AI's ability to effectively lower learning barriers in design, its use in teaching also entails certain risks and challenges that may negatively affect student learning.

AI-generated responses may sometimes contain inaccurate information, or provide seemingly plausible explanations for incorrect answers. Such "AI hallucinations" introduce knowledge bias and mislead students [31,32]. Beginners, lacking sufficient background knowledge to discern information, are more prone to trusting and reinforcing incorrect concepts, thereby undermining learning outcomes [33]. On the other hand, the accuracy and consistency of AI feedback are limited by biases in its training data, making it prone to errors when handling edge cases or culturally specific knowledge. For example, Mbalaka [34] found that DALL-E 2 exhibited notable difficulty in generating detailed images of "African families" compared to more generic "family" images. This could amplify students' stereotypes and lead to biases in culturally diverse environments.

More seriously, over-reliance on generative AI may deprive students of opportunities for critical thinking and deep problem-solving, thereby diminishing student learning engagement [35] and affecting the cultivation of higher-order thinking. The convenience of AI may sometimes suppress active exploration, as students may tend to directly copy AI output rather than think independently, potentially affecting the development of originality and deep learning capabilities [36]. Since design is a practical activity, excessive reliance on GenAI in design courses may hinder students' proficient mastery of fundamental design skills, as designers may directly adopt AI-provided solutions rather than actively adjusting and constructing generated results based on their own needs [37]. This process lacks critical evaluation and sustained reflection on AI-generated results, further impeding the formation of independent design thinking and creative problem-solving abilities among design students [38].

Furthermore, research by Barcaui [39] indicates that ChatGPT may serve as a cognitive "crutch"; while unrestricted use of ChatGPT can enhance immediate learning outcomes, it significantly impairs long-term knowledge retention. Text generated by tools such as ChatGPT may also blur the boundaries between original work and automatically generated content, increasing the risk of plagiarism [40,41].

It is evident that the long-term effects of ChatGPT in education still require further validation and empirical research. Therefore, this study, while introducing GenAI into design courses to examine student learning outcomes, also attends to the risks and negative effects of AI use.

2.4. Research Questions and Hypotheses

Based on the research gaps identified above, this study proposes the following research questions and hypotheses.

RQ1 (Perceived Process Efficacy): In hardware-driven design courses, does generative AI assistance improve students' perceived task completion efficiency and self-reported achievement of stage-specific goals?

H1: *Under AI-assisted conditions, students' perceived task completion efficiency and self-reported stage goal attainment are higher than under non-AI conditions.*

RQ2 (Learning Outcomes): Do the process efficacy gains afforded by generative AI extend to improvements in knowledge transfer and application ability?

H2: *Under AI-assisted conditions, students' self-assessed ability to transfer and apply knowledge are higher than under non-AI conditions.*

RQ3 (Learning Experience): Does generative AI assistance improve students' overall learning experience and satisfaction?

H3: *Under AI-assisted conditions, students report a more positive overall learning experience and higher satisfaction.*

RQ4 (Learning Difficulties): Does the introduction of generative AI change the intensity, quantity, and types of difficulties encountered by students during the learning process?

H4: *Under AI-assisted conditions, students report lower perceived difficulty intensity, fewer total difficulties, and different difficulty type distributions compared to non-AI conditions.*

RQ5 (Switching Costs): Are the adaptation costs of switching between AI and non-AI conditions symmetric?

H5: *Students' adaptation costs of switching between the two conditions are symmetric; that is, switching costs are symmetric across directions.*

3. Course Design and AI-Assisted Pedagogy

3.1. Course Overview

This study was conducted through a professional elective course entitled "IoT Hardware and Design Innovation" offered to undergraduates at the School of Design, Hunan University. The course is publicly listed in the undergraduate industrial design curriculum and available course catalog. The industrial design undergraduate program at the School of Design, Hunan University (conferring a Bachelor of Engineering degree) is oriented toward industry development trends such as smart manufacturing and "Internet Plus" (a national strategy promoting the integration of internet technologies across industries), emphasizing systematic mastery of modern design theory, methods, and tools under new technological conditions, as well as the cultivation of interdisciplinary collaboration and practical innovation capabilities. As part of this undergraduate curriculum, the "IoT Hardware and Design Innovation" course is oriented toward universal connectivity and enhancing quality of life, centering on the IoT system implementation pathway with microcontrollers at its core, covering key components including information sensors, devices, gateways, and servers. Through smart connected terminal products and front-end interaction and visual design tasks, students are guided to approach user experience and product innovation from the technical chain of IoT smart product design and development, integrating real-world application scenarios, while also discussing topics such as electronic product design in the dual-carbon era.

3.2. Teaching Content

Regarding the technical dimension, the primary reference textbook was *The Internet of Things Illustrated* (authored by NTT DATA Group, translated by Ling Ding, 2017). This textbook was selected primarily for its high degree of versatility and pedagogical suitability: it adopts a standard layered architecture (perception layer, network layer, platform layer, and application layer), which is broadly applicable to various scenarios including smart homes,

industrial monitoring, and smart cities, with good interoperability and scalability capable of effectively supporting heterogeneous device access and data interaction. The course presents technical elements through abundant illustrations and progressively scaffolded approaches, covering sensor types, transmission protocols, prototype platform selection and circuit connections, data analysis, and linkage with smartphones or wearable devices, enabling learners to quickly comprehend and engage in hands-on practice while making abstract technical concepts more accessible.

Building upon this foundation, a core feature of the course requires students to learn and construct a complete IoT technology chain. The instructor provides pedagogical guidance from a data flow perspective, helping students understand the end-to-end pathway from the physical world to the user interface. The IoT system pathway in this course was designed as follows: environmental data was initially captured by sensors, then processed and transmitted wirelessly via an Espressif ESP32 microcontroller. These data were routed to an EMQX message broker using the MQTT protocol, with the server-side CentOS system ensuring data persistence through Redis caching and database storage. Finally, the information was rendered through a front-end visualization interface for end-user interaction. The ESP32 was selected as the hardware platform because it supports the Arduino programming language familiar to industrial design students, lowering the entry barrier for embedded development; MQTT and EMQX were selected as the messaging middleware because the lightweight characteristics of the MQTT protocol are naturally suited for low-bandwidth, high-concurrency data transmission in IoT scenarios. During the server environment setup phase, students were required to utilize hosts provided by the research team to personally deploy EMQX, Redis, and database services on the CentOS system, thereby constructing a private cloud server. This process spanned students' learning across multiple knowledge domains including embedded hardware, network communication protocols, server-side operations, and front-end development, embodying a full-stack engineering practice approach. Students needed to understand and master the basic framework of such IoT systems (see Figure 1) to provide technical support for subsequent design projects.

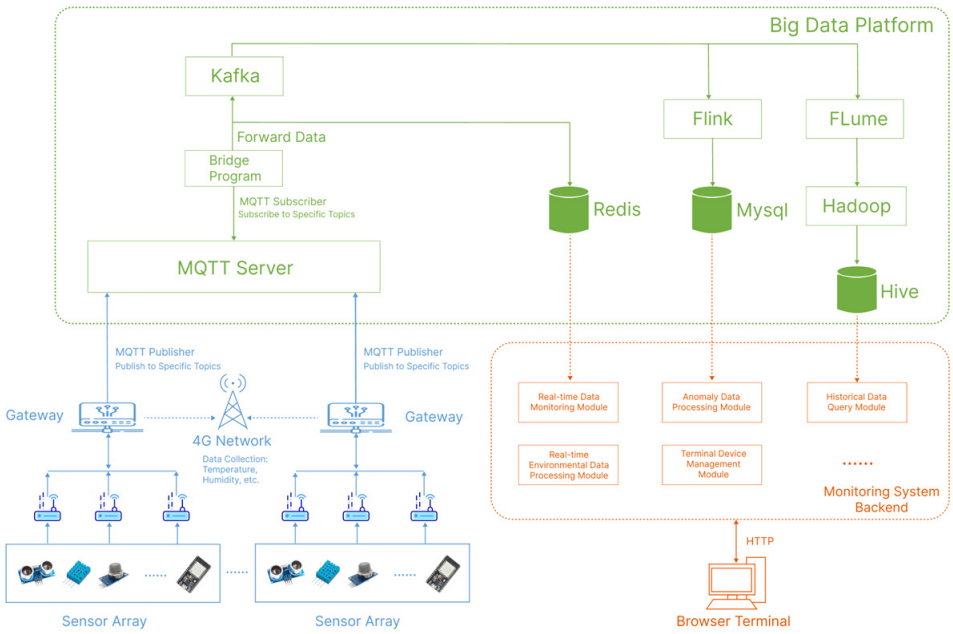


Figure 1. Basic framework of the IoT system studied in this course.

The course was structured into two modules. The first, a technical practice module (the focus of the present study), required students to build a complete end-to-end IoT data

pipeline and develop engineering capabilities spanning from the perception layer through to the application layer. The second, an integrated design application module, required students to integrate their acquired technical knowledge into IoT product design proposals, including problem definition, concept generation, system architecture, and prototype delivery. The crossover experiment was conducted within the technical practice module.

3.3. AI Chat Tool-Assisted Pedagogy

This study introduced a pedagogical approach assisted by a generative AI chat tool (ChatGPT) (see Figure 2), which utilizes the generative AI chatbot to assist students in IoT hardware-related design courses. The AI flexibly assumed multiple roles including technical tutor, creative stimulator, and solution discussant based on students' questions. Due to resource constraints, every two students shared a single OpenAI account with access to the ChatGPT-4o model. Each student operated within a distinct, separate chat window, and the cross-session memory feature was explicitly disabled; consequently, this configuration was functionally equivalent to the use of independent accounts. During the crossover experimental phase, all tasks were completed by students working independently; the research team maintained continuous supervision throughout the entire task period, strictly prohibiting students within the same group from engaging in mutual discussion or viewing each other's chat windows. This learning method encompassed four key stages: "Information Provision", "Problem Formulation", "Discernment" and "Adoption or Follow-up Inquiry".

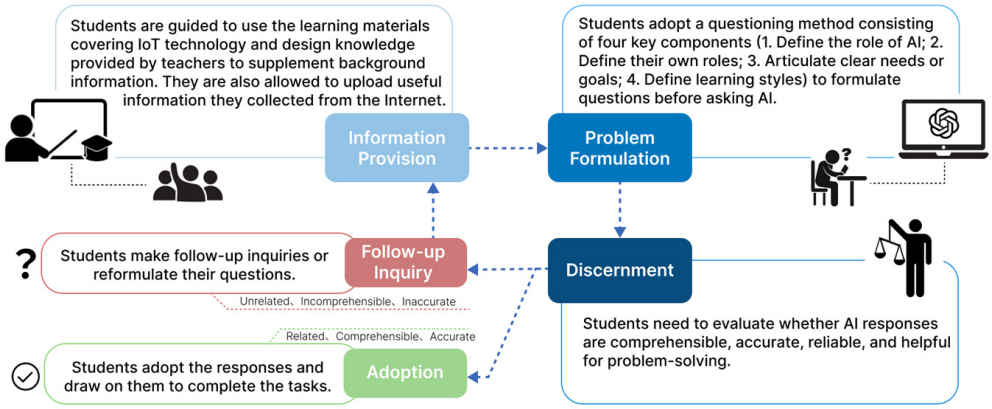


Figure 2. AI-assisted learning method.

In the "Information Provision" stage, students were permitted to upload learning materials containing IoT technology and design knowledge provided by the teaching team, and they were also allowed to independently screen and upload various information sources including text, images, files, and web links to supplement ChatGPT's background knowledge.

In the "Problem Formation" stage, the research team particularly emphasized the importance of questioning methods and conducted training on questioning approaches for each student before the course began (see Figure 3). This questioning method encompasses four key components: (1) ChatGPT Persona, (2) User Persona, (3) Topic Details, (4) Learning Style. This prompting approach references the work of Sagar [42] and is considered effective in enhancing AI's performance in answering questions.

In the "Discernment" stage, students needed to evaluate whether ChatGPT's responses were correct, reasonable, and comprehensible. If accepted, they entered the "Adoption" stage for information reprocessing and application; if not accepted, they entered the "Follow-up Inquiry" stage, supplementing relevant information and re-asking questions until the problem was resolved or confirmed to be currently unsolvable.

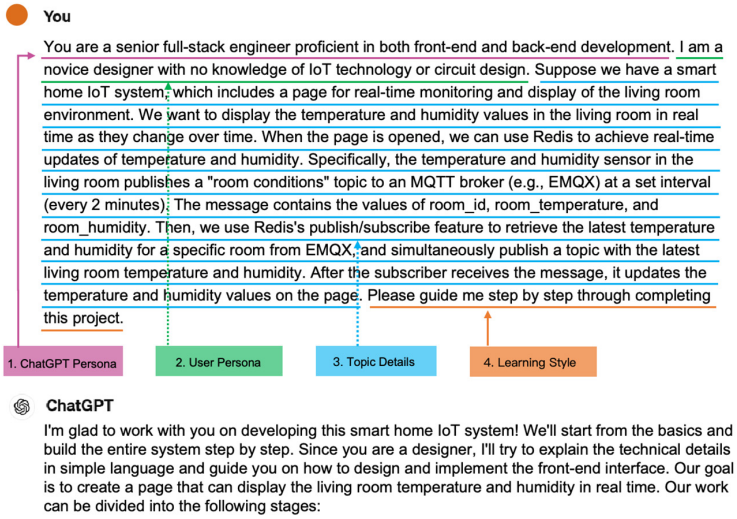


Figure 3. Questioning method with four key components.

4. Research Methods

4.1. Participants and Research Setting

Twelve third-year students from the industrial design program at the School of Design, Hunan University, participated in this study. Eligible participants were all enrolled in the standard four-year bachelor's program in industrial design and had no prior learning or development experience related to IoT hardware technology; graduate students and students from other programs were excluded.

This study was approved by the Ethics Committee of the School of Design, Hunan University (Ethics Approval Number: 2024015). This study does not constitute a clinical treatment trial and therefore did not require registration with a clinical trial registry. All participants signed an informed consent and confidentiality agreement, completed multiple assessment tasks and the full final deliverable, and received a research participation stipend provided by the research team upon conclusion of the study.

This study was conducted face-to-face from November 2024 to January 2025 in a classroom provided by the School of Design, Hunan University, see Figure 4. To ensure experimental fairness, all participants' learning activities were carried out under the supervision of the research team, which strictly enforced the experimental constraints (e.g., prohibiting AI use during designated phases of the experiment).



Figure 4. Participants and research environment.

4.2. Learning Conditions

Learning Materials Available Under Traditional Learning Conditions: Participants were permitted to use traditional learning resources, including the textbook *The Internet of Things Illustrated* (authored by NTT DATA Group, translated by Ling Ding, 2017), instructor lecture notes, and system architecture diagrams. Students were permitted to use computers to consult non-AI digital resources (e.g., Google search or the CSDN forum), but all AI-based platforms—including chatbots of any kind, literature reading and summarization tools, and browser-embedded AI assistants—were explicitly prohibited. These learning materials reflect typical pre-AI-era self-directed learning practices, in which students would use textbooks, summary notes, and non-AI-driven online searches for learning and task completion. This setup was chosen to present a realistic and practical learning environment for fair comparison with the AI-assisted learning condition. When students confirmed that they were unable to independently resolve a problem, they were permitted to seek help from the instructor or teaching assistants.

Learning Materials Available Under AI Chat Tool-Assisted Learning Conditions: in addition to all traditional learning resources available under the control condition, the experimental group was additionally permitted to use the ChatGPT-4o large language model (released by OpenAI in 2024). Every two students shared an OpenAI account with access to ChatGPT-4o, and students could access the online version of ChatGPT (https://chatgpt.com, Access Date: 1 February, 2025) provided by OpenAI directly through electronic devices. This reflected typical and authentic AI-era learning practice activities—rather than a mutually exclusive binary choice between traditional learning methods or AI tool-assisted methods, students could freely choose to use traditional learning materials, seek AI assistance, or combine both. When students confirmed that they were unable to independently resolve a problem, they were likewise permitted to seek help from the instructor or teaching assistants.

4.3. Crossover Experiment Design

This study employed a replicated crossover design. Based on the knowledge domains commonly involved in IoT learning, six stage tasks were designed around IoT perception-layer device integration and data acquisition, data stream processing and service deployment, and application-layer visualization delivery, all within a private cloud server environment. These six stages were organized into three crossover pairs (Pair 1: Stages 1–2; Pair 2: Stages 3–4; Pair 3: Stages 5–6), with each pair forming a within-pair controlled comparison. The three pairs varied systematically in difficulty level and assessment focus, collectively covering the complete IoT engineering pipeline—from perception-layer integration, through cloud data ingestion and service API deployment, to application visualization and delivery. This design simulated a real-world IoT project and was intended to train and evaluate students' hands-on IoT engineering competencies (see Table 1).

Before the first experimental task, the 12 students were organized into six two-person administrative units solely for the purpose of OpenAI account allocation and crossover sequence assignment; these units did not collaborate on any tasks during the crossover phase mentioned in this article. They were required to finish their tasks alone (see Section 3.3). Each unit randomly obtained a number from 1 to 6 through an online random number generator, which determined their crossover sequence: units assigned odd numbers (1, 3, 5) followed the AB sequence (AI first, then traditional), while units assigned even numbers (2, 4, 6) followed the BA sequence (traditional first, then AI). Throughout the phased training process, all students completed tasks individually under instructor supervision, and the learning resources available to them were determined solely by the condition assigned for that particular session.

Table 1. Overview of Crossover Task Design Across Six Stages.

Pair	Stage	IoT Layer	Task Focus	Core Activities	Completion Criteria
1	1	Perception & Edge Acquisition	Sensor integration & telemetry publishing	Identify PM2.5 sensor model/interface; implement data acquisition on ESP32 (Arduino IDE); publish JSON readings to MQTT topic dorm/pm25.	Serial output + broker logs confirm valid continuous data; publish rate, continuity, time-to-first-reading assessed.
	2		Edge-side threshold alerting	Extend ESP32 pipeline with threshold logic (T > 33 °C or RH > 53%); publish alarm payload to MQTT broker.	Broker logs confirm reliable alerts under threshold conditions; alert correctness, latency, and telemetry stability evaluated.
2	3	Ingestion Pipeline & Service Layer	Cloud ingestion & persistence	Configure EMQX broker to receive PM2.5 messages; use Rule Engine to forward telemetry to Redis (state) and Kafka (streaming, topic: dorm_sensor_pm25).	End-to-end delivery confirmed in broker logs and downstream consumers; message rate, Rule Engine config correctness, data format compliance checked.
	4		Backend API development	Implement Spring Boot service reading PM2.5 from Redis; expose RESTful API endpoints for front-end consumption.	API returns correct PM2.5 JSON consistently; response latency, request stability, Redis read/deserialize robustness assessed.
3	5	Application Visualization & UX Refinement	Front-end integration & UI adjustment	Modify existing dashboard: adjust chart *x*-axis font size; integrate with backend API for dynamic real-time data refresh.	UI change reflected correctly; data pulls and refreshes via API successfully; time-to-completion and refresh stability evaluated.
	6		Advanced visualization & UX enhancement	Visualize 2 h DHT22 time series with ECharts; refine aesthetics (dark-mode, gradients); add interactivity (tooltips, animations); implement responsive layout.	Dashboard renders time series with interactive affordances across viewport sizes; clarity, interactivity, responsiveness, and modern UI adoption evaluated.

Note. Each pair comprises two tasks at the same IoT layer, administered in counterbalanced order across groups. All tasks were completed within a 30 min time constraint.

The study organized tasks using a replicated crossover approach: each pair of adjacent stages constituted an AB/BA crossover unit, with students switching learning conditions (AI ↔ traditional) between these two tasks, thereby simultaneously controlling for individual differences and stage/task differences within the same group of participants. Specifically, when under the traditional condition, students could only use non-AI learning resources provided by the course, such as the textbook *The Internet of Things Illustrated*, technical forums similar to CSDN, and traditional browser searches, with any generative AI platforms or their alternatives strictly prohibited; when under the AI condition, students could additionally use the designated AI tool for learning and problem-solving support. The conditions were then switched at the start of the next task, alternating progressively across consecutive stages (see Figure 5).

To reduce the influence of time investment differences on subjective load and performance, each crossover task was limited to 30 min; additionally, to mitigate the immediate carryover influence of the preceding learning condition, the minimum washout period between any two crossover tasks exceeded 24 h. Through these arrangements, this study was able to assess the average effects of AI-assisted learning relative to traditional learning

approaches across different task foci and difficulty levels, and examine their consistency across multiple crossover units.

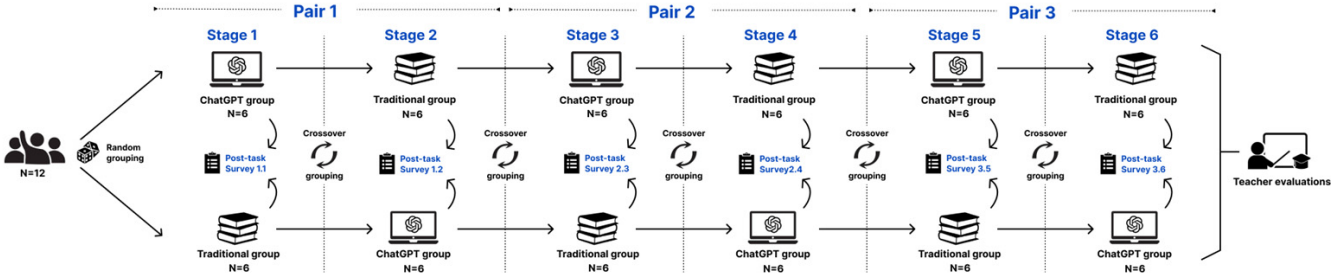


Figure 5. Randomized crossover grouping method.

The randomized crossover method is a key feature of this study. In traditional parallel-group designs, the experimental group may consistently develop expectancy effect from being "selected" (e.g., feeling they are the "focus group" and exerting more effort and confidence), or the control group may develop resentful demoralization from "not being selected"; in a crossover design, both groups have experimental and control opportunities, balancing the bias introduced by group identity and making the assessment of intervention effects purer, reflecting only the effects of AI rather than inherent group differences. Furthermore, single assessments may be affected by random factors (e.g., a group happening to be in a good learning state on a particular day or being coincidentally familiar with certain knowledge points); multiple repeated crossovers can offset such randomness, yielding more robust estimates of intervention effects. Additionally, to fully utilize the sample size, having the same group of students serve as both experimental and control groups effectively obtains double the data (within-subject control data + between-group control data) with the same sample size, yielding higher statistical power. After careful deliberation, we ultimately selected this randomized crossover design, aiming to minimize inter-group differences, mitigate randomness, and control participant-level confounding factors.

4.4. Measurement Instruments

Upon completion of each stage task, students completed an approximately 5 min stage assessment questionnaire, which recorded immediate experiences and task completion under different learning conditions in a repeated-measures fashion. The questionnaire design drew upon several established theoretical frameworks and scales in the field of educational technology, including the measurement approach of "perceived usefulness" from the Technology Acceptance Model (TAM) [43], the item phrasing of the "Self-Efficacy for Learning and Performance" subscale from the Motivated Strategies for Learning Questionnaire (MSLQ) [44], the measurement logic of the "Satisfaction" dimension from the ARCS Motivational Model (ARCS) [45], and the research tradition of subjective load assessment from Cognitive Load Theory (CLT) [46]. Items were contextually adapted to align with the pedagogical objectives of the IoT hardware-driven design course and the structural requirements of the crossover design. The quantitative section primarily employed a five-point Likert scale (1 = strongly disagree or very low, 5 = strongly agree or very high). All scale items were collaboratively developed by three researchers with dual expertise in educational technology and design education, and revised following pilot testing.

The questionnaire employed a conditional branching design: students first indicated whether they were assigned to use AI tools in the current stage, after which they were routed to the AI-condition or non-AI-condition item branch. Core measurement items across the two branches (task efficiency, task experience, difficulty types, etc.) used identically worded parallel items to support paired comparisons between conditions; additionally,

each branch contained condition-specific items (e.g., "perceived helpfulness of AI tools" under the AI condition, and "sufficiency of non-AI methods" under the non-AI condition). The questionnaire also included several universal items answered by all participants regardless of condition branch (e.g., goal attainment, self-assessed knowledge transfer, peer comparison judgments).

The Stage 1 questionnaire served as the baseline version (Supplementary Materials). From Stage 2 onward, two additional between-stage comparison items were introduced: switching adaptation ("adaptation when switching from the previous stage's learning approach to the current stage") and relative effectiveness ("whether the current stage's learning approach is more effective compared to the previous stage"). Consequently, the Stage 2–6 questionnaires contained two more items than Stage 1, with item numbering offset from that point. This paper uniformly references item numbers from the Stage 2–6 questionnaire version, the mapping of each item to research questions is presented in Table 2.

Table 2. Mapping of Stage Assessment Questionnaire Items to Research Questions and Hypotheses.

RQ/H	Dimension	Item No. (Stages 2–6)	Item No. (Stage 1)	Item Content	Scale Type	Applicable Condition
RQ1/H1	**Task Efficiency and Goal Attainment**					
	Stage goal attainment	Q5	Q4	I believe the stage goals have been achieved for me	5-point Likert (Strongly disagree–Strongly agree)	Universal
	Subjective task efficiency	Q13 (AI)/Q22 (Non-AI)	Q12/Q20	In this stage, I felt my task completion efficiency was	5-point Likert (Very low–Very high)	Condition-branched
	Peer efficiency comparison	Q10	Q9	I believe classmates using AI in this stage completed tasks more efficiently than those not using it	5-point Likert (Strongly disagree–Strongly agree)	Universal
RQ2/H2	**Knowledge Transfer and Application**					
	Self-assessed knowledge transfer	Q6	Q5	I believe I can apply the knowledge learned in this stage to practical problems	5-point Likert (Strongly disagree–Strongly agree)	Universal
	Peer ability comparison	Q11	Q10	I believe classmates using AI in this stage gained more knowledge and ability improvement than those not using it	5-point Likert (Strongly disagree–Strongly agree)	Universal
RQ3/H3	**Learning Experience and Resource Evaluation**					
	Overall satisfaction	Q9	Q8	My overall satisfaction with the learning experience in this stage is	5-point Likert (Very dissatisfied–Very satisfied)	Universal
	Task process experience	Q15 (AI)/Q23 (Non-AI)	Q14/Q21	In this stage, my experience of completing the task was	5-point Likert (Very poor–Very good)	Condition-branched
	Learning resource satisfaction	Q14 (AI)/Q20 (Non-AI)	Q13/Q18	Satisfaction with AI tool helpful-ness/Satisfaction with teacher-provided learning resources	5-point Likert (Very dissatisfied–Very satisfied)	Condition-branched
	Relative effectiveness	Q17 (AI)/Q25 (Non-AI)	N/A (Stages 2–6 only)	Compared to the previous stage, is the current stage's learning approach more effective	5-point Likert (Significantly more effective–Clearly less effective)	Condition-branched

Table 2. *Cont.*

RQ/H	Dimension	Item No. (Stages 2–6)	Item No. (Stage 1)	Item Content	Scale Type	Applicable Condition
			Difficulty Intensity, Count, and Types			
RQ4/H4	Learning obstacle intensity	Q7	Q6	I encountered significant learning obstacles in this stage	5-point Likert (Strongly disagree–Strongly agree)	Universal
	Difficulty type distribution	Q16 (AI)/Q24 (Non-AI)	Q15/Q22	The main difficulties I encountered in this stage were	Multiple-choice	Condition-branched
			Switching Adaptation Costs			
RQ5/H5	Switching adaptation	Q4	N/A (Stages 2–6 only)	My adaptation when switching from non-AI to AI (or vice versa) was	5-point Likert (Very difficult to adapt–Very easy to adapt)	Universal
	Perceived AI tool helpfulness	Q12	Q11	AI tools helped my learning in this stage	5-point Likert (Strongly disagree–Strongly agree)	AI condition
	Non-AI sufficiency	Q21	Q19	Without AI tools, are other methods sufficient to help me complete the task	5-point Likert (Completely insufficient–More than sufficient)	Non-AI condition
	Non-AI learning strategies	Q18	Q16	Approaches mainly relied on to complete the task	Multiple-choice	Non-AI condition
	Most helpful resource	Q19	Q17	Which of the following was most helpful for completing the learning task	Single-choice	Non-AI condition

Task completion, efficiency perception, and self-assessed knowledge transfer. This dimension assessed students' self-evaluation of task progression performance and learning outcomes at each stage, comprising three items: stage goal attainment, perceived task efficiency, and self-assessed knowledge transfer and application. These items were presented with parallel wording under AI and non-AI conditions. The goal attainment and efficiency perception items were informed by the core concept of "perceived usefulness" from the Technology Acceptance Model [43]. Item wording was further adapted from the "Self-Efficacy for Learning and Performance" subscale of the MSLQ [44]. The knowledge transfer item ("I believe I can apply the knowledge learned in this stage to practical problems") captured students' immediate judgment of the transferability of acquired knowledge. When pooled across both conditions (n = 72), the goal attainment and efficiency perception items yielded Cronbach's α = 0.873, indicating high internal consistency. The knowledge transfer item was analyzed as a standalone indicator and was excluded from the above reliability calculation.

Learning experience and resource evaluation. This dimension captured students' overall learning experience and their subjective evaluation of support resources at each stage. Both conditions shared two common items: "overall satisfaction" and "task process experience". Condition-specific items were also included: the AI condition probed perceived AI helpfulness and satisfaction, whereas the non-AI condition probed perceived support from instructor/course resources and a sufficiency judgment ("whether non-AI methods alone were adequate to complete the task"). The common items were designed with reference to the "Satisfaction" dimension of ARCS Motivational Model [45]. Combined common items (n = 72) yielded Cronbach's α = 0.834; the AI experience subscale (4 items, n = 36) yielded Cronbach's α = 0.829; the non-AI resource experience subscale (4 items, n = 36) yielded Cronbach's α = 0.837.

Learning difficulties and perceived learning obstacles. This dimension captured the intensity of perceived learning obstacles and the structure of difficulties encountered. It comprised both quantitative and qualitative components. The quantitative item assessed perceived learning obstacle intensity on a five-point scale, designed against the theoretical background of CLT [46]. After reverse scoring, this item showed high correlations with goal attainment ($r = 0.854$, $p < 0.001$) and efficiency perception ($r = 0.810$, $p < 0.001$), indicating good consistency with the overall process experience dimension. The qualitative component used structured multiple-choice items to record the main types of difficulties students encountered—task comprehension, slow technical problem-solving, inability to verify information authenticity, inability to find effective resources, and insufficient time—along with their frequencies. These data were used to compare the number, type distribution, and structural shifts in reported difficulties across conditions.

Peer comparison judgments. This dimension comprised two items asking students to judge whether "classmates using AI completed tasks more efficiently than those not using it" and whether "classmates using AI gained more knowledge and ability improvement than those not using it". Together, these items captured students' collective perception of AI's relative advantages from a peer-observer perspective. The Spearman correlation between the two items was 0.335 ($p = 0.004$), indicating that they tapped related but distinguishable constructs; accordingly, each was reported as an independent indicator in subsequent analyses.

Switching adaptation costs. This dimension was designed to capture the subjective costs of condition switching and shifts in approach preference within the crossover design. Beginning in Stage 2, two items were introduced: "degree of adaptation when switching from the previous stage to the current stage" (five-point scale) and "whether the current stage's approach is more effective than the previous stage's" (five-point scale). The design of this dimension was inspired by the attention to sequence effects in crossover trial methodology [47]; both items were treated as independent indicators in analyses.

Beyond the dimension-level reporting, this study further examined the internal consistency of core process indicators unified across conditions. This indicator set comprises five items: goal attainment, obstacle perception (reverse scored), overall satisfaction, efficiency perception, and experience perception. Given that the stage questionnaire was administered repeatedly to the same learner across 6 task stages, observations are non-independent. To avoid overestimating internal consistency by treating repeated observations as independent samples, this study reports two estimates simultaneously:

(1) Merged all-observation estimate: Combining observations across 6 stages ($n = 72$) yielded Cronbach's $\alpha = 0.928$; each item's corrected item-total correlation was no less than 0.67, indicating high consistency with the total score and stable contribution to the overall indicator.

(2) Conservative individual-averaged estimate: Computing means across 6 measurements per learner ($n = 12$) yielded Cronbach's $\alpha = 0.905$, serving as a conservative reference after controlling for non-independence.

Both estimates indicate good internal consistency for this core indicator set, supporting its use as a process-level indicator for within-subject comparisons and mechanism discussions in the classroom context. Considering that this questionnaire was administered in a repeated-measures fashion across 6 stages, and that parallel subscales under both AI and non-AI conditions yielded α values exceeding 0.82, we consider this questionnaire to possess acceptable measurement reliability within this course context. It should be noted that this questionnaire is a contextualized instrument, and its further psychometric properties (e.g., factor structure stability and measurement invariance) remain to be validated in larger samples and multi-course contexts.

4.5. Data Analysis

All quantitative analyses were conducted at the student level. For each student, mean scores under AI and non-AI conditions were computed separately for each measure, and paired-samples *t*-tests were used to compare differences between conditions. Non-parametric Wilcoxon signed-rank test results were also reported as robustness checks; the exact test was used when paired differences contained no zero values and sample size permitted, otherwise the normal approximation was applied. Effect sizes were reported as paired Cohen's dz and Hedges' g. For the analysis of difficulty type distributions, each multiple-choice option was converted to a binary indicator (selected = 1, not selected = 0), and selection proportions under AI and non-AI conditions were computed at the student level before paired comparisons. For switching adaptation cost analysis, stages where "the current learning condition differed from the previous stage" were defined as switch events, with comparisons made between two switching directions: Non-AI → AI and AI → Non-AI. Statistical analyses were conducted using Python 3.12.3 (scipy, pingouin), with significance level set at $\alpha = 0.05$.

5. Results

5.1. H1: Perceived Process Efficacy

5.1.1. Perceived Task Completion

Participants' perceived stage goal attainment ratings (Q5) under AI-assisted conditions (M = 3.64, SD = 0.59) were higher than under non-AI conditions (M = 2.56, SD = 0.90). After computing each student's mean score under each condition, a paired-samples *t*-test revealed a significant difference, t(11) = 4.98, $p < 0.001$, mean difference = 1.08, 95% CI [0.60, 1.56]. The effect size was large (paired Cohen's dz = 1.44; Hedges' g = 1.34). The non-parametric test yielded consistent results (Wilcoxon signed-rank test, $p = 0.005$). This indicates that participants' perceived stage goal attainment was significantly higher under AI-assisted conditions, as shown in Figure 6.

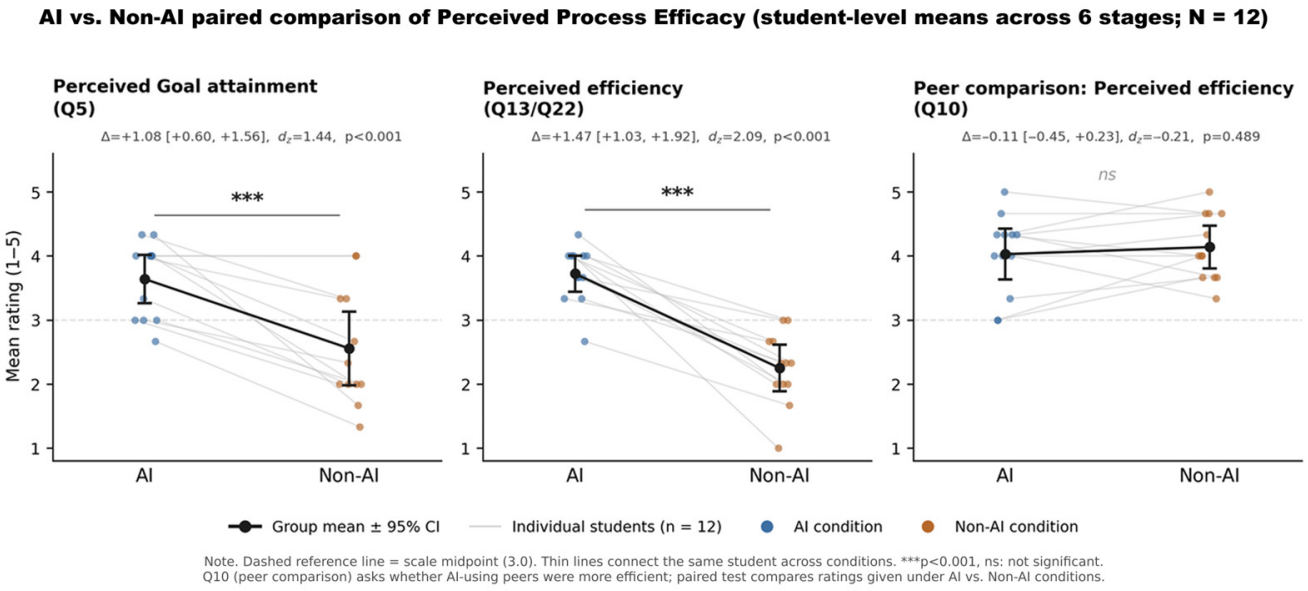


Figure 6. Paired Comparison of Perceived Process Efficacy Indicators Between AI and Non-AI Conditions.

5.1.2. Perceived Task Completion Efficiency

Students' subjective efficiency ratings under AI-assisted conditions (Q13) were significantly higher than under non-AI conditions (Q22) (AI: M = 3.72, SD = 0.45; Non-AI: M = 2.25, SD = 0.57). The paired-samples *t*-test indicated a significant difference between

conditions, t(11) = 7.26, $p < 0.001$; mean difference = 1.47, 95% CI [1.03, 1.92]. The effect size was large (paired Cohen's dz = 2.09; Hedges' g = 1.94), indicating that AI-assisted conditions conferred a clear advantage in students' perceived task completion efficiency.

5.1.3. Peer Comparison of Perceived Task Completion Efficiency

On the peer comparison dimension for perceived efficiency (Q10), participants showed high overall agreement. After averaging each student's ratings across six stages, the mean Q10 score was 4.08 (SD = 0.51), significantly above the neutral point of 3, t(11) = 7.36, $p < 0.001$ (paired Cohen's dz = 2.12). To further examine whether this judgment was influenced by the individual's current learning condition, students' mean Q10 scores were computed separately under AI and non-AI conditions and compared via paired test. The difference was not significant (AI: M = 4.03, SD = 0.63; Non-AI: M = 4.14, SD = 0.52), t(11) = −0.72, $p = 0.489$, indicating that this peer comparison judgment was consistent across conditions. This suggests that nearly all students tended to agree that "classmates using AI were more efficient", and this result was not influenced by whether the student was personally using AI in the current stage, as also shown in Figure 6.

5.2. H2: Learning Outcomes

5.2.1. Knowledge Transfer and Application Ability

Participants' self-assessed knowledge transfer and application ability (Q6) was slightly higher under AI-assisted conditions than under non-AI conditions (AI: M = 3.22, SD = 0.50; Non-AI: M = 3.08, SD = 0.79; see Figure 7). After computing each student's mean score under each condition, a paired-samples *t*-test indicated no significant difference between conditions, t(11) = 0.59, $p = 0.564$, mean difference = 0.14, 95% CI [−0.38, 0.65]. The effect size was small (paired Cohen's dz = 0.17; Hedges' g = 0.16). The non-parametric test yielded consistent results (Wilcoxon signed-rank test, $p = 0.602$).

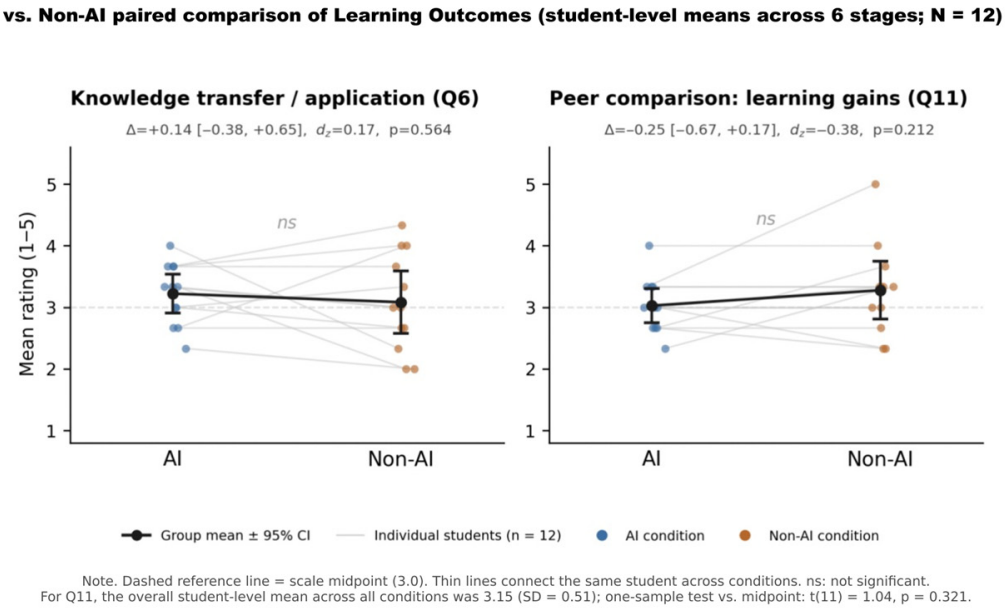


Figure 7. Paired Comparison of Learning Outcome Indicators Between AI and Non-AI Conditions.

5.2.2. Peer Comparison of Knowledge Transfer and Application Ability

On the peer comparison dimension for knowledge transfer and application ability (Q11, "I believe that classmates using AI in this stage gained more knowledge and ability improvement than those not using it"), the overall participant rating was 3.15 (SD = 0.51), not significantly different from the neutral point of 3, t(11) = 1.04, $p = 0.321$ (paired Cohen's dz = 0.30). To further examine whether this judgment was influenced by the individual's

current learning condition, students' mean Q11 scores were computed separately under AI and non-AI conditions and compared via paired test. The difference was not significant (AI: M = 3.03, SD = 0.44; Non-AI: M = 3.28, SD = 0.74), t(11) = −1.33, p = 0.212, suggesting that this peer comparison judgment was consistent across learning conditions. The results did not provide sufficient statistical evidence to support participants significantly agreeing that "the AI group gained more in ability" (the mean was close to the neutral point and the confidence interval spanned neutral/zero difference), indicating that this judgment had not yet formed a stable consensus.

5.3. H3: Learning Experience

5.3.1. Overall Satisfaction

Regarding overall satisfaction (Q9), participants' ratings were higher under AI-assisted conditions than under non-AI conditions (AI: M = 3.61, SD = 0.40; Non-AI: M = 3.00, SD = 0.78; see Figure 8). After computing each student's mean score under each condition, a paired-samples t-test revealed a significant difference, t(11) = 2.39, p = 0.036, mean difference = 0.61, 95% CI [0.05, 1.17]. The effect size was medium-to-large (paired Cohen's dz = 0.69; Hedges' g = 0.64). The non-parametric test yielded consistent results (Wilcoxon signed-rank test, p = 0.041).

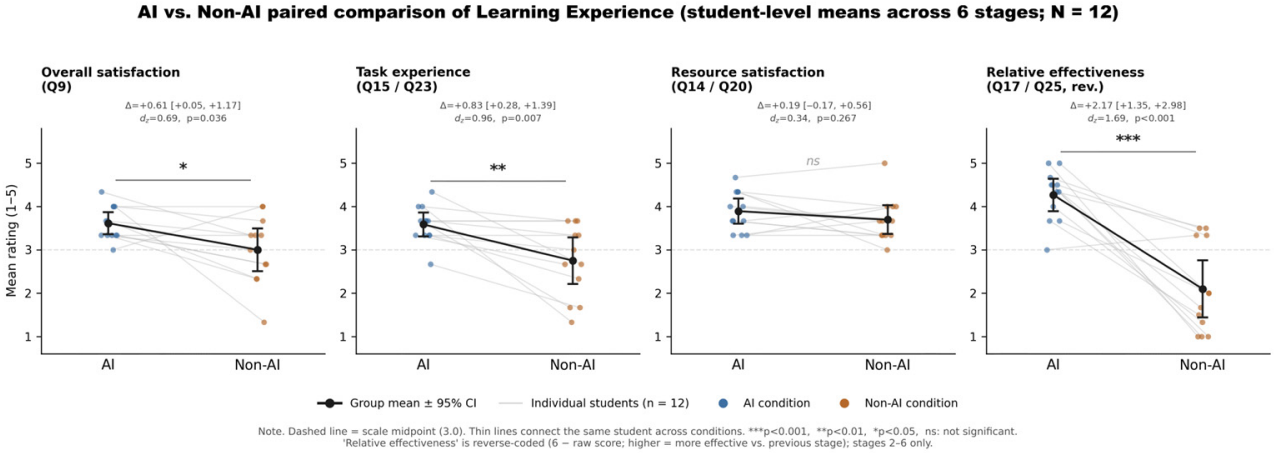


Figure 8. Paired Comparison of Learning Experience Indicators Between AI and Non-AI Conditions.

5.3.2. Task Process Experience

Participants' task experience ratings under AI-assisted conditions (Q15) (M = 3.58, SD = 0.43) were higher than under non-AI conditions (Q23) (M = 2.75, SD = 0.84). The paired-samples t-test indicated a significant difference between conditions, t(11) = 3.32, p = 0.007, mean difference = 0.83 (95% CI [0.28, 1.39]). The effect size was large (paired Cohen's dz = 0.96; Hedges' g = 0.89). As a robustness check, the Wilcoxon signed-rank test yielded p = 0.008, consistent with the t-test. This indicates that participants had a better task experience under AI-assisted conditions.

5.3.3. Satisfaction of Learning Resource

Participants' learning resource satisfaction ratings under AI-assisted conditions (Q14) (M = 3.89, SD = 0.46) were slightly higher than under non-AI conditions (Q20) (M = 3.69, SD = 0.52). The paired-samples t-test indicated no significant difference, t(11) = 1.17, p = 0.267, mean difference = 0.19, 95% CI [−0.17, 0.56]. The effect size was small (paired Cohen's dz = 0.34; Hedges' g = 0.31). This result indicates that although the means trended in favor of the AI condition, the difference in participants' satisfaction with the two types of learning resources did not reach statistical reliability given the current sample size.

5.3.4. Relative Effectiveness of Learning Resources

To compare the relative effectiveness of different learning approaches compared to the previous stage, this study used items Q17 (AI condition) and Q25 (non-AI condition). Because the original scale was reverse-coded (higher values indicating worse), scores were reverse-coded prior to analysis (i.e., 6 minus the raw score), so that higher values indicate higher perceived effectiveness. Given that the item stem referenced "compared to the previous stage", this analysis included only data from Stages 2–6, with student-level mean scores computed separately for AI and non-AI conditions. Results showed that effectiveness ratings under the AI condition were significantly higher than under the non-AI condition (AI: M = 4.26, SD = 0.59; Non-AI: M = 2.10, SD = 1.03). The paired-samples *t*-test indicated a significant difference, t(11) = 5.84, $p < 0.001$, mean difference = 2.17, 95% CI [1.35, 2.98]. The effect size was very large (paired Cohen's dz = 1.69; Hedges' g = 1.57). This result suggests that, compared to traditional learning resources, participants were more inclined to perceive AI-assisted learning as bringing more noticeable effectiveness gains across stages, as also shown in Figure 8.

5.4. H4: Learning Difficulties

5.4.1. Perceived Intensity of Learning Difficulties

Regarding the perceived intensity of learning difficulties encountered (Q7), participants' ratings were significantly lower under AI-assisted conditions than under non-AI conditions (AI: M = 2.75, SD = 0.41; Non-AI: M = 3.83, SD = 0.61). After computing each student's mean score under each condition, a paired-samples *t*-test revealed a significant difference, t(11) = −5.38, $p < 0.001$, mean difference (AI − Non-AI) = −1.08, 95% CI [−1.53, −0.64]. The effect size was very large (paired Cohen's dz = 1.55; Hedges' g = 1.44). The non-parametric test yielded consistent results (Wilcoxon signed-rank test, $p = 0.003$). This indicates that participants encountered substantially fewer learning difficulties under AI-assisted conditions than under non-AI conditions.

5.4.2. Types of Learning Difficulties Encountered

(1) Differences in Difficulty Count across Learning Conditions

Difficulty count (number of selected difficulties) was used to characterize the number of difficulty types self-reported by students in each task. Results showed that the number of difficulties reported under AI-assisted conditions was significantly fewer than under non-AI conditions: an average of 1.75 difficulty types were selected per task under AI conditions(Q16), compared to 2.53 under non-AI conditions(Q24). The paired-samples *t*-test indicated a significant difference, t(11) = −3.44, $p = 0.006$, mean difference (AI − Non-AI) = −0.78, 95% CI [−1.28, −0.28]. The effect size was large (paired Cohen's dz ≈ -0.99), indicating that AI assistance can reduce the overall difficulty burden during the learning process.

(2) Proportion of Each Difficulty Type across Conditions

To further identify shifts in difficulty sources, each multiple-choice option was converted to a binary indicator (selected = 1, not selected = 0), and student-level selection proportions (0–1) were computed separately for AI and non-AI conditions across repeated tasks. Results revealed a divergent pattern (see Figure 9): difficulties related to resource retrieval and problem-solving speed decreased significantly under AI-assisted conditions, while concerns related to information reliability emerged. Specifically, the selection proportions for "unable to find effective learning resources" and "slow technical problem-solving" were significantly higher under non-AI conditions; conversely, "unable to verify content authenticity" was selected at a significantly higher rate under AI conditions. The remaining

difficulty types (e.g., insufficient time, task comprehension) did not differ substantially between conditions.

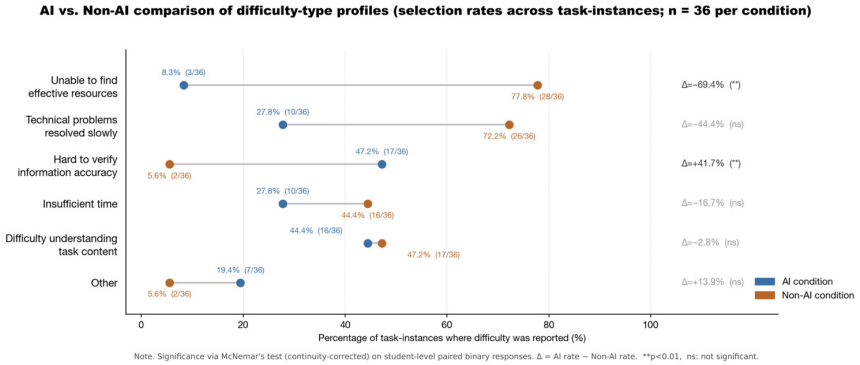


Figure 9. Difficulty-Type Profile Across AI and Non-AI Conditions.

The open-text responses from the "Other (please specify)" option in the multiple-choice items were not fully preserved during the platform export process; therefore, this study only conducted quantitative analysis of the occurrence proportion of "Other" as a category and did not perform thematic analysis. Future research may supplement more complete qualitative evidence by preserving original text records.

Results indicate that AI assistance did not simply reduce all difficulties but rather shifted difficulties from the "resource retrieval and problem-solving speed" level to the "information reliability assessment" level.

5.5. H5: Switching Costs

5.5.1. Comparison of Adaptation Across Switching Directions

To assess adaptation during learning condition switches, this study used item Q4 (1–5 scale, higher scores indicating better adaptation). Considering that not all stages involved a learning condition switch, this study defined stages where "the current learning condition differed from the previous stage" as switch events, distinguishing between two switching directions: Non-AI → AI and AI → Non-AI. Results showed that students' adaptation ratings during Non-AI → AI switches were significantly higher than during AI → Non-AI switches (Non-AI → AI: M = 4.21, SD = 0.62; AI → Non-AI: M = 2.00, SD = 1.19). The paired-samples *t*-test indicated a significant difference, $t(11) = 6.85$, $p < 0.001$, mean difference = 2.21, 95% CI [1.50, 2.92]. The effect size was very large (paired Cohen's dz = 1.98). The non-parametric test yielded consistent results (Wilcoxon signed-rank test, $p = 0.00049$), confirming the robustness of this difference. Results suggest that participants experienced higher adaptation costs when switching from AI back to traditional resources, indirectly reflecting a subjective preference for AI-assisted approaches, see Figure 10.

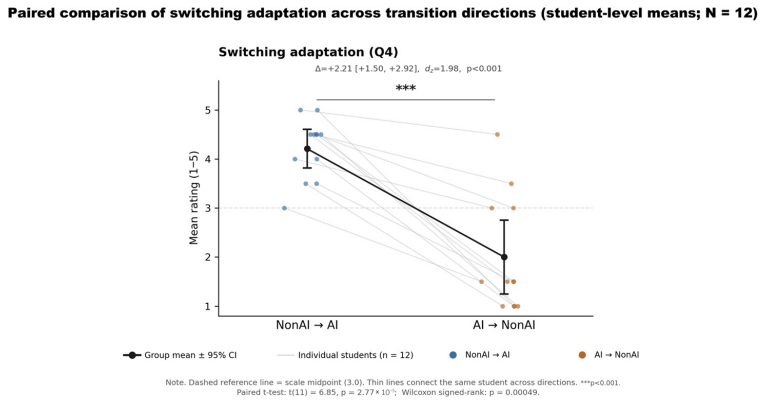


Figure 10. Paired Comparison of Switching Adaptation Ratings Across Transition Directions.

5.5.2. Perceived Helpfulness of AI Tools Under AI Conditions

Regarding the perceived helpfulness of AI tools under AI conditions (Q12, "AI tools helped my learning in this stage"), participants' overall ratings were high (M = 4.11, SD = 0.38). After averaging each student's ratings across AI-condition stages (n = 12), a one-sample t-test against the neutral point of 3 showed that this rating was significantly above 3, t(11) = 10.00, $p < 0.001$, mean difference = 1.11, 95% CI [0.87, 1.36]. The effect size was very large (paired Cohen's dz = 2.89; Hedges' g = 2.69), indicating that participants under AI-assisted conditions broadly perceived AI tools as providing significant help to their learning.

5.5.3. Sufficiency of Non-AI Resources for Task Completion

Regarding "task completion sufficiency" under non-AI conditions (Q21, "Without AI tools, are other methods sufficient to help me complete this stage's classroom tasks"), participants' overall ratings were below the neutral level (M = 2.42, SD = 0.77). After averaging each student's ratings across non-AI-condition stages (n = 12), a one-sample t-test against the neutral point of 3 showed that this rating was significantly below 3, t(11) = −2.63, p = 0.023, mean difference = −0.58, 95% CI [−1.07, −0.10]. The effect size was medium-to-large (paired Cohen's dz = −0.76; Hedges' g = −0.71). This result suggests that participants generally tended to perceive the "sufficiency" of completing stage tasks using only non-AI methods as inadequate.

5.5.4. Learning Strategies Adopted Under Non-AI Conditions

Under non-AI conditions, learning strategies (Q18) exhibited a clear pattern of "self-directed retrieval + independent attempts". At the task level (36 non-AI task records), "consulting internet resources/forums/technical documentation" had the highest selection rate (86.1%), followed by "independent thinking and attempting to solve problems" (66.7%) and "referencing course handouts/sample resources" (55.6%); "seeking help from classmates" (11.1%) and "seeking teacher guidance" (5.6%) appeared less frequently. Students typically combined multiple strategies to complete tasks, with an average of 2.25 methods selected per task under non-AI conditions (student-level M = 2.25, SD = 0.78). For "most helpful resource" (Q19, single-choice), "consulting internet resources/forums/technical documentation" had the highest proportion (55.6%), followed by "course handouts/cases/sample code/provided learning materials" (22.2%), "teacher guidance and instruction" (11.1%), "independent thinking and attempting to solve problems" (8.3%), and other (2.8%), as shown in Figure 11.

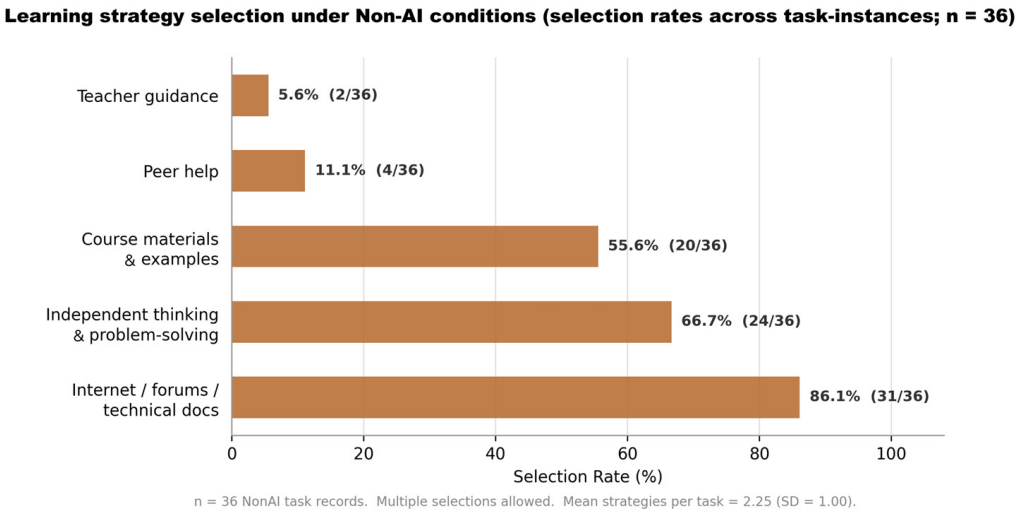


Figure 11. Selection Rates of Learning Strategies Under Non-AI Conditions.

5.6. Summary

(1) Perceived Process Efficacy: H1 supported. Under AI conditions, students' perceived stage goal attainment ($p < 0.001$, paired Cohen's dz = 1.44) and subjective efficiency ($p < 0.001$, paired Cohen's dz = 2.09) were both significantly higher than under non-AI conditions, with large effect sizes. Peer comparison judgments were consistent: students broadly agreed that "classmates using AI were more efficient" (M = 4.08), and this judgment was not influenced by the individual's current condition ($p = 0.489$).

(2) Learning Outcomes: H2 not supported. Students' self-assessed knowledge transfer and application ability under AI conditions did not differ significantly from non-AI conditions ($p = 0.564$, paired Cohen's dz = 0.17). On the peer comparison dimension, the rating for "the AI group gained more in ability" did not differ significantly from the neutral point of 3 ($p = 0.321$).

(3) Learning Experience: H3 supported. Overall satisfaction ($p = 0.036$, paired Cohen's dz = 0.69) and task process experience ($p = 0.007$, paired Cohen's dz = 0.96) were both significantly better under AI conditions. Learning resource satisfaction did not differ significantly between conditions ($p = 0.267$). Students' relative effectiveness ratings for AI-assisted learning were significantly higher than for non-AI conditions ($p < 0.001$, paired Cohen's dz = 1.69).

(4) Learning Difficulties: H4 supported. Perceived difficulty intensity under AI conditions was significantly lower than under non-AI conditions ($p < 0.001$, paired Cohen's dz = 1.55), and the total number of difficulties was also significantly reduced ($p = 0.006$, paired Cohen's dz = −0.99). The two conditions exhibited different patterns in difficulty type distributions: the selection proportions for "unable to find effective learning resources" and "slow technical problem-solving" were significantly higher under non-AI conditions; the selection proportion for "unable to verify content authenticity" was significantly higher under AI conditions.

(5) Switching Costs: H5 not supported (adaptation costs were asymmetric). Adaptation ratings when switching from non-AI to AI (M = 4.21) were significantly higher than when switching from AI back to non-AI (M = 2.00), with the difference being highly significant ($p < 0.001$, paired Cohen's dz = 1.98). Additionally, under AI conditions, students broadly perceived AI tools as helpful to their learning (M = 4.11, $p < 0.001$), while under non-AI conditions, students' ratings of "whether non-AI methods alone were sufficient to complete tasks" were significantly below the neutral point (M = 2.42, $p = 0.023$).

6. Discussion and Limitations

6.1. Process Gains Are Consistently Perceived but Bounded: Faster and Smoother, Yet Not Necessarily Deeper

The clearest signal from the randomized crossover phase was AI's consistent facilitation of perceived task progress: efficiency and attainment improved significantly, learning experiences became smoother, and perceived learning barriers decreased. These gains offered substantial support to interdisciplinary learners with no prior IoT background. Previously, IoT tasks such as environment configuration and data integration were often difficult to initiate due to significant gaps in background knowledge and insufficient instructional materials. Although we had provided students with detailed textbooks such as *The Internet of Things Illustrated* and configuration manuals compiled by the research team, students still struggled to comprehend these materials due to their substantial knowledge gaps, and the materials could not anticipate or address every problem they encountered. AI, however, can synthesize fragmented information and provide step-by-step clarification as just-in-time support, addressing each learner's specific questions and reducing the time spent stuck on problems. This finding is consistent with the results of

Kazemitabaar et al. [48] regarding adolescent programming novices. They found that in AI-assisted programming tasks, students lacking programming experience were able to complete tasks more successfully, with AI functioning as a form of "just-in-time scaffolding" that helped novices bridge the initial knowledge gap. In the review of engineering education, Bravo and Cruz-Bohorquez [49] also noted that AI chatbots demonstrate significant advantages in helping students rapidly acquire background knowledge, particularly in interdisciplinary tasks where students lack prior knowledge.

It should be acknowledged that this study employed an open-label design in which participants were aware of their assigned condition, and that the AI condition provided objectively richer resources than the traditional condition. The low efficiency and satisfaction ratings observed under non-AI conditions may therefore partially reflect perceived resource inadequacy rather than solely the absence of AI's instructional effect, and the very large effect sizes reported for H1 and H3 should be interpreted with this context in mind. At the same time, it is worth noting that for interdisciplinary learners with no prior technical background, the willingness to engage with unfamiliar engineering tasks—and the relative confidence to persist rather than retreat—is itself a pedagogically significant outcome. Research by Pan and Harun on programming anxiety has shown that affective barriers can significantly reduce learners' engagement and performance levels [28]; if AI assistance helps lower these barriers and enables design students to approach hardware debugging, network configuration, or server deployment with greater willingness, the resulting reduction in affective obstacles constitutes a meaningful educational gain, even if it cannot be cleanly separated from cognitive facilitation at this stage. Future research employing more granular behavioral measures (e.g., attempt frequency, error-correction sequences) may help disentangle the motivational and cognitive components of AI-assisted process gains.

However, the aforementioned process-level gains, whether stemming from cognitive facilitation or the alleviation of emotional barriers, did not automatically translate into stable improvements in knowledge transfer and application ability. Self-assessed transfer/application ability (Q6) showed no significant difference between the two conditions ($p = 0.564$), and the peer comparison dimension (Q11) similarly did not deviate from the neutral point ($p = 0.321$). In other words, AI likely increased the probability of "pushing tasks to completion" but did not necessarily foster the formation of "internalized knowledge structures and transferable understanding".

This finding is highly consistent with the large-scale field experiment published in PNAS by Bastani et al. [50]: students using GPT-4 performed significantly better than the control group during practice, but when AI was removed, their exam scores were actually lower. It should be noted that the "non-significant effect" of AI on ability transfer in our study may be related to our short-duration task format. The meta-analysis by Wang and Fan [51] found that ChatGPT's positive impact on learning performance had a large effect size, but that experimental duration was a key moderating variable, with 4–8 weeks of sustained use producing more significant effects than short-term use. This suggests that in 30 min time-limited tasks, AI is more likely to serve immediate task progression rather than deeper, more structured understanding. A deeper analysis of the cognitive mechanisms underlying this disconnect—such as cognitive offloading effects and changes in germane cognitive load—falls beyond the scope of this paper's focus on process-level findings and may be further explored in future research with longer-duration data and expanded theoretical frameworks.

6.2. Difficulty Restructuring Rather than Elimination

From the perspective of Cognitive Load Theory, the decrease in the number and severity of perceived difficulties under AI-assisted conditions appears valid. This is highly consistent with the experimental results of Stadler et al. [52], who randomly assigned 91 university students to use either ChatGPT or Google search for scientific information retrieval tasks. They found that students using LLMs had significantly lower cognitive load than the traditional search group; however, despite the reduced cognitive load, these students ultimately produced lower-quality argumentation with shallower reasoning depth—a phenomenon the team summarized as "cognitive ease at a cost".

However, our research data reveals a more consequential structural shift than mere difficulty reduction: difficulties shifted from those related to task progression (such as "unable to find resources" and "slow problem-solving") toward concerns about information reliability and verifiability. AI does not simply "reduce burden" but rather redistributes it: offloading part of the extraneous cognitive load (retrieval, screening, organizing expression) while pushing learners toward higher-order epistemic demands—judging whether information is reliable and whether it is appropriate for the current context. Taken together with research of Evans et al. [53], AI effectively reduces extraneous cognitive load, but may simultaneously diminish germane cognitive load directly related to deep learning. Reducing extraneous load facilitates learning, but if technology simultaneously diminishes germane cognitive load, it negatively impacts deep engagement—precisely the risk that requires vigilance in AI-assisted learning contexts.

In traditional learning processes, such verification work seems to account for a relatively small share of the learning process, because once learners find specific information in professional forums, tutorials, or literature, they can generally treat it as trustworthy—because its credibility has already been validated by credible external authorities (such as large numbers of forum users, tutorial reviewers, peer-review experts, etc.). Unlike traditional information sources, AI output lacks external trust mechanisms such as peer verification and community review. Zhai et al. [54] noted that learners face the dilemma of being unable to determine whether AI-generated content cites credible sources when using generative AI systems, which places greater demands on their ability to independently evaluate and verify information accuracy. In AI-generated contexts, such evaluation requires additional searching and cross-checking. More importantly, for true interdisciplinary beginners with no prior foundation, this kind of verification may not even be feasible: without AI's explanatory mediation, they may be unable to understand the information they are confronted with at all, and any error in the AI's interpretive processing may cause this already fragile chain of reasoning to collapse. The empirical work of Athaluri et al. [55] further demonstrated that among 178 AI-generated references, 69 lacked DOIs and 28 were completely unverifiable: AI presented entirely fabricated academic sources in highly professional formats, and such "false information presented within a credible-looking framework" is extremely difficult for learners lacking domain knowledge to identify.

This aligns closely with our research context. In hardware-driven IoT tasks, students with a design background are in the position of "most needing AI help but least equipped with verification ability". Real engineering problems are highly sensitive to specific parameters, environmental constraints, and system context; even if AI's answers appear correct, they may "fail to run" at the implementation level. Therefore, the key educational challenge under AI-assisted conditions has shifted toward the cultivation of learners' verification capacity—this is not merely a simple technical information-checking skill, but a higher-order competence requiring learners to possess sufficient domain knowledge to judge whether AI output is compatible with specific engineering constraints and system contexts.

This shift from retrieval difficulty to verification difficulty is, at its core, an information literacy problem—one that a growing body of research on GenAI and misinformation in education has begun to address. Fulsher et al. [56] systematically reviewed how GenAI serves as both a source of and a solution to misinformation across educational levels, identifying three key themes: identifying misconceptions, prebunking, and (re)producing misinformation. Among the reviewed studies, Church [57] found that even after considerable discussion in class on hallucinations, students who used ChatGPT to complete essay assignments still produced work containing fabricated information and unverified sources. This pattern directly mirrors the difficulty restructuring identified in this study: when AI removes retrieval barriers, the locus of challenge shifts to evaluating the trustworthiness of AI-generated outputs, a competency that current pedagogical designs have yet to systematically address.

6.3. Asymmetric Switching Costs and Dependency Risks

Learning resource switching in the crossover phase exhibited significant asymmetry: Non-AI → AI transitions were nearly seamless, while AI → Non-AI transitions produced notable subjective withdrawal costs. As early as 1983, in the classic study "Ironies of Automation" in the industrial automation domain, Bainbridge [58] noted that when humans are in a prolonged state of automated monitoring/dependence, critical abilities such as manual skills and parameter adjustment timing may atrophy from disuse, making "taking over" even more difficult when truly needed. This is consistent with our finding of higher adaptation costs when "returning from AI to the traditional resource system".

This asymmetry can be understood as a mild "technology withdrawal reaction". After using AI, learners' cognitive processes and emotional regulation have become partially embedded in the AI tool; sudden removal produces the dual shock of process disruption and loss of security. The key here is not "banning AI" but "how to remove the scaffold". Scaffolding theory, proposed by Wood et al. [30], emphasizes that instructional support should be dynamically adjusted as learner competence develops. Van de Pol et al. [59] identified "fading" as one of the core features of scaffolding: scaffolds should gradually decrease in intensity and frequency as learner independence grows, enabling learners to progressively assume more responsibility and ultimately achieve independence. However, current AI educational tools generally lack such calibrated fading mechanisms: in actual classrooms, AI is either continuously available as an always-on default resource providing full-function support, or completely disabled at some point—both extremes deviate from the gradualism required by fading theory. The "sudden switch" in our crossover design was essentially a non-gradual scaffold removal, and the resulting high adaptation costs precisely validate the importance of the fading principle.

Therefore, if the educational goals of the course aim for students to experience interdisciplinary knowledge transfer and hands-on hardware-driven design tasks, then by all means let AI help extensively; but if the course educational goal aims to cultivate genuine knowledge understanding and transferable competence—forming knowledge structures and engineering thinking that are explainable, verifiable, and transferable—then mechanisms for staged "de-dependency" must be designed. Specifically, "de-dependency" strategies such as independent reiteration of key steps, AI-free debriefing sessions, and restricting AI to verification rather than direct problem-solving are essentially the deliberate embedding of "calibrated fading" nodes within AI-empowered environments, transforming dependency risk from an inevitable consequence into a manageable pedagogical variable.

6.4. Implications

The above findings point to four specific recommendations. The first three focus on pedagogical design at the course level, while the fourth addresses a broader institutional perspective on responsible AI adoption.

First, verification literacy should be cultivated as a core component. AI does indeed resolve the most painful difficulties for interdisciplinary learners—insufficient background knowledge, terminology barriers, low retrieval efficiency. However, when these task-progression difficulties disappear, a new category of difficulty emerges: learners must judge whether the information AI provides is trustworthy, whether it is compatible with the current hardware conditions, and whether it will fail to run in actual deployment. This shift from "unable to find" to "unable to discern" essentially raises the cognitive demands—but most learners, especially those students with no prior knowledge, are unprepared for this upgrade. This signals to educators that course design cannot simply introduce AI and stop there; it must simultaneously embed verification ability cultivation components. For example, requiring students to manually verify AI-suggested circuit designs, annotate their comprehension level line-by-line for AI-generated code, or challenge AI-proposed solutions in group discussions—making "questioning AI" an institutionally encouraged learning behavior rather than one omitted under the pressure of efficiency.

Second, calibrated scaffold fading could be deliberately implemented throughout the course. The asymmetric switching costs observed in this study were produced by abrupt condition changes inherent to the crossover design; no graduated fading protocol was implemented or evaluated. Nevertheless, the magnitude of the observed adaptation gap motivates the following pedagogical proposition, which we offer as a theoretically grounded recommendation for future course design and empirical validation: students adapted nearly seamlessly when switching from traditional resources to AI, but the reverse switch—from AI back to independent resources—produced a notable adaptation gap. This suggests that once AI's emotional support and cognitive convenience are embedded into the learning process, it is no longer an external device that can be unplugged at any time, but more like a foundational service already integrated into the operating system: removing it means not just functional loss, but a wholesale readjustment of the entire work rhythm and psychological expectations. Instructors need to plan the fading tempo of scaffolds as carefully as a guide planning a descent route: not suddenly disabling AI at some point, but gradually narrowing AI's available scope as the course progresses. For example, a three-stage progression could be implemented: Stage 1 permits unrestricted AI interaction; Stage 2 restricts AI to verification-oriented queries to validate student-generated logic without direct solution generation; and Stage 3 mandates independent task completion prior to AI-facilitated review. Such incremental adjustments ensure that dependency mitigation is not an abrupt withdrawal, but rather a calibrated, learner-adaptable fading process. This three-stage framework remains an untested proposition. Future research can implement and evaluate such graduated fading protocols to determine whether they effectively mitigate the dependency risks identified in this study.

Third, the potential role of AI as a mediating artifact in peer interaction warrants further exploration. Although the crossover tasks in this study were completed individually and student pairing was an administrative arrangement for shared account access rather than a designed collaborative intervention, we informally observed outside the crossover task sessions that students within the same class spontaneously shared AI-generated solutions and debugging strategies with peers during the broader course activities, with AI outputs occasionally serving as shared reference points in these exchanges. This observation, while not captured by the present study's measurement instruments, suggests that AI may function not only as a vertical scaffold between instructor and learner but

also as a horizontal mediating artifact that shapes peer-to-peer knowledge negotiation. Bronfenbrenner's [60] ecological perspective on learning environments and van Lier's [61] interactionist account of scaffolding in collaborative settings provide relevant theoretical lenses for investigating this dimension. Future research could design studies that systematically examine how AI-generated content mediates peer interaction and whether such mediation constitutes a distinct form of peer scaffolding.

Fourth, institutional-level responsible GenAI adoption deserves parallel attention. The present study focused on classroom-level pedagogical design, but the challenges identified here, including verification difficulty, dependency formation, and reliance on a proprietary commercial platform, are inseparable from broader institutional considerations. These challenges should not be viewed exclusively as pedagogical design variables; they are part of the larger discussion about how to implement GenAI responsibly within educational institutions.

In particular, our finding that AI restructures the difficulty landscape toward information verification (Section 5.4) exemplifies precisely the kind of systemic information literacy challenge that requires what Kamińska [62] termed an "institutional mechanism" rather than ad hoc measures. Her Strategic Mitigation Framework for Responsible GenAI Adoption in Academic Libraries addresses such challenges through four strategic pillars—AI Literacy & Education, Governance & Policy, Green AI Procurement & Deployment, and Open-Source & Collaborative Ecosystems—while navigating a four-dimensional trade-off space encompassing Cost, Carbon, Equity, and Trust. Especially relevant to our findings is her emphasis on formal governance and policy adoption structures (such as Mandatory Transparency and Data Provenance, and Human-in-the-Loop Workflows) as institutional mechanisms for managing epistemic reliability threats in academic settings. As discussed in Section 6.2, the shift from retrieval difficulty to verification difficulty is fundamentally an information literacy problem; addressing it at scale therefore requires moving beyond individual course design toward institutional AI literacy infrastructure.

Among the institutional experiences informing this framework, Michalak et al. [63] documented how academic libraries operationalize ethical, inclusive, and pedagogically sound AI adoption through practical strategies spanning contract negotiation, data privacy, accessibility, training, among others, aligned with evolving AI literacy frameworks. Indeed, the present study itself illustrates several of these dimensions in practice: embedding a commercial LLM as a curricular scaffold raises practical questions of access equity (not all institutions or students can sustain subscription costs), data privacy (student interaction logs reside on third-party servers), and environmental sustainability (the carbon footprint of large-scale LLM inference). Situating our findings within this broader discourse clarifies the position we wish to advance: the difficulty restructuring and dependency risks documented here are not merely pedagogical design problems to be solved at the classroom level, but early indicators of systemic challenges that require coordinated institutional responses. In this transition, academic libraries—increasingly recognized as primary agents of change in establishing AI literacy frameworks at universities globally, are poised to play a central role.

6.5. Limitations

This study has several limitations.

First, the primary outcome measures in the crossover experimental phase—including task completion efficiency, goal attainment, and learning experience—rely on self-report instruments. This design choice reflects the process-level orientation of the research questions, which focus on how students perceive their efficiency, what difficulties they encounter, and how they adapt to condition switching rather than on product-level performance output. The completion criteria outlined in Table 1 are inherently binary (e.g., sensor data either

publishes to the broker or it does not; an API either returns valid JSON or it fails), and the six crossover tasks span heterogeneous IoT layers, tools, and debugging contexts, making it difficult to construct a cross-task-comparable objective scoring rubric within the scope of this exploratory study. Such self-reported data can reflect learner perceptions and classroom processes but may also be influenced by individual differences, daily states, and subjective judgments of task difficulty. Although all cross-tasks in this study were conducted under the continuous supervision of the research team and observational evidence suggested that students' self-assessed progress efficacy ratings largely aligned with their actual task progress observed during the sessions, all efficacy-related findings should be interpreted as reflecting learners' subjective perceptions of progress rather than objectively verified performance differences. Future research may develop more granular objective instruments suited to progressive engineering debugging tasks, enabling triangulation of subjective and objective indicators.

Second, the sample size was small (n = 12). Although the crossover design allowed each participant to serve as both experimental and control group, generating 72 observation-level data points across 6 task stages that partially compensated for the limited number of participants, the sample size still constrains statistical power and generalizability of results; subsequent research needs to replicate and validate these findings with larger samples and multiple cohorts. Additionally, because the crossover-phase tasks were primarily practical IoT engineering tasks (e.g., server configuration, data collection and analysis), which are difficult to objectively quantify like standardized tests, multiple assessment indicators relied on students' subjective reports (e.g., perceived efficiency, experience, obstacle perception). Such data can reflect learner perceptions and classroom processes but may also be influenced by individual differences, daily states, and subjective judgments of task difficulty.

Third, the crossover design itself may involve order and carryover effects: experience accumulated by students in previous task rounds (e.g., familiarity with task procedures, anticipation of common errors, understanding of tool workflows) will inevitably influence subsequent performance. Even though a statistical advantage for the AI condition was observed, it must be acknowledged that practice effects may contribute; future research can further control this influence through more rigorous counterbalancing and more homogeneous, equally difficult tasks.

Beyond the above core methodological limitations, the following boundary conditions are also worth noting.

Fourth, task completion in the crossover experimental phase did not count toward students' course grades. While this arrangement helped reduce the interference of assessment anxiety on experimental results, it may also have weakened some students' task engagement. This means the AI-assisted effects observed in this study may carry a conservative bias—that is, in actual teaching scenarios where tasks carry higher stakes, the effect differences brought by AI assistance may be more pronounced.

Fifth, this study's characterization of AI usage patterns was insufficiently fine-grained. Different students may vary considerably in their AI usage frequency, question quality, verification strategies, and usage positioning (treating AI as a retrieval tool versus a reasoning partner), but constrained by the course cycle and data collection conditions, these process variables (e.g., conversation logs, prompt types, iteration counts, verification behaviors) have not yet been systematically quantified. This limits our ability to further address "which usage patterns produce gains or risks"—we will endeavor to fill this gap in subsequent research.

Sixth, the granularity of open-text collection for the "Other" option in the difficulty multiple-choice question was insufficient to support systematic qualitative coding. Future

research may supplement interviews, learning journals, or more complete open-text collection designs to strengthen qualitative evidence supporting "difficulty restructuring" (from retrieval and problem-solving to verification and discernment).

Seventh, this study was conducted in a Chinese-medium instruction environment, and students' interactions with ChatGPT-4o were primarily in Chinese. Although GPT-4o possesses relatively mature Chinese processing capabilities, large language models typically have richer training data in English corpora; therefore, generalization of this study's results to other linguistic environments should be approached with caution.

This study focused on AI's process effects and difficulty structure changes. Deeper learning mechanisms related to AI use (cognitive load structure, technology acceptance, learning engagement) and the quality structure of outputs under universal AI use conditions will be further explored in subsequent research with different research questions and independent data sources.

7. Conclusions

This study originated from a specific pedagogical predicament: when "Deploy or Die" has become the benchmark narrative of contemporary design education, how can industrial design students break through technical barriers such as "weak programming foundations" and "insufficient hardware knowledge" to continuously progress and complete engineering tasks in interdisciplinary IoT courses? Generative AI appears to offer a highly attractive pathway—but does this pathway eliminate learning difficulties, or redistribute them elsewhere? Through a randomized crossover experimental design, we examined the effects of generative AI (ChatGPT-4o) on the learning process in an "IoT Hardware and Design Innovation" course for undergraduate industrial design students. Twelve third-year students with no IoT technology background alternated between AI-assisted and traditional learning resources across six short-cycle engineering tasks. The study addressed five hypotheses and yielded three findings.

First, AI's perceived efficacy as a process-level scaffold is clear and reliable in this context. Across the three dimensions of perceived efficiency, self-reported attainment, and learning experience, AI conditions were significantly superior to traditional conditions with large effect sizes. For design students lacking hardware technology backgrounds, AI effectively lowered the entry barrier for interdisciplinary learning. However, self-assessed knowledge transfer and application ability showed no between-condition differences, suggesting that improvements in process efficiency should not be equated with the internalization of deep competence.

Second, AI altered the morphology of learning difficulties rather than simply eliminating them. The total number of difficulties did indeed decrease, but difficulty types underwent a structural shift—difficulties related to resource retrieval decreased significantly, while difficulties related to information verification increased significantly. We term this "difficulty restructuring", which reveals the structural transformation of learning challenges in the AI era: old barriers are leveled, but new barriers emerge elsewhere.

Third, switching adaptation costs were highly asymmetric. Switching from traditional resources to AI was nearly "painless", but the reverse switch produced a significant adaptation gap, revealing emerging dependency risks following AI's embedding into the learning process. This finding provides an empirical foundation for the design of scaffolding fading strategies in educational contexts.

Taken together, these three preliminary findings converge on a working judgment that warrants replication: in hardware technology-driven interdisciplinary design education, the role of generative AI in this context more closely resembles a "difficulty restructurer" rather than a "difficulty eliminator"—it significantly reshapes the learning process but

does not automatically guarantee deeper learning outcomes. AI redistributes cognitive demands from the retrieval and problem-solving level to the discernment and verification level, while silently generating new path dependencies in the process of reducing perceived learning obstacles and enhancing task experience.

Based on these findings, we recommend simultaneously advancing two pathways in AI-enhanced hardware-driven design courses: cultivating verification literacy to counter the cognitive risks brought by difficulty restructuring, and implementing calibrated scaffold fading to counter path dependency. Only in this way can the "process liberation" brought by AI be genuinely converted into learners' independent knowledge construction and engineering thinking capabilities. These classroom-level strategies, however, will need to be situated within broader institutional frameworks for responsible GenAI adoption that navigate the interconnected dimensions of cost, carbon, equity, and trust, with academic libraries playing a central role in establishing AI literacy infrastructure for this transition.

This study has clear limitations, including a small sample size, short-cycle task design, a single AI model (ChatGPT-4o), single-language environment and insufficient characterization of AI usage patterns. Future research may replicate the above findings with larger samples and longer teaching cycles, and introduce AI conversation logs and process behavioral data to more precisely track the relationships between different AI usage strategies and learning outcomes. Furthermore, deeper learning mechanisms related to AI use—including changes in the internal structure of cognitive load, the interaction between technology acceptance and learning engagement, and the structural characteristics of course output quality when AI becomes a default resource—will be further explored in subsequent research with independent research questions and data sources.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/app16083946/s1, File S1: Stage Task Assessment Questionnaire 1·Stage 1; File S2: Stage Task Assessment Questionnaire 2·Stages 2–6 (with Crossover Comparison Items).

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