# AI-Driven Instructional Design of Digital Textbooks for Computer Science Education: Supporting Teachers and Personalized Learning

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## Abstract

*The purpose of this study is to propose an instructional model that improves high school first-year classes by applying the principles of Cognitive Load Theory to the key features of the Codle AI digital textbook (e.g., AI Tutor, AI Quiz Generator, Course Recommendation, Learning Dashboard). The proposed model is structured in a three-phase format—Introduction, Development, and Conclusion—based on the theoretical framework of intrinsic, extraneous, and germane cognitive load. The methodology involved applying the Codle platform to an actual class and conducting qualitative interviews with first-year students at a general high school to explore the effectiveness of the model. The main findings indicate that features such as the AI Tutor and Course Recommendation reduced confusion, adjusted task difficulty to appropriate levels, and increased self-directed learning through immediate feedback. These results suggest that the structured integration of AI digital textbook functionalities can optimize students' cognitive load and enhance learning engagement.*

## 1. Introduction

In the field of education, the introduction of AI-powered digital textbooks aims to realize personalized learning tailored to each learner's level. In South Korea, starting in 2025, AI digital textbooks will be gradually introduced across core subjects—English, Mathematics, and Computer Science—for students in elementary grades 3–4, middle school grade 1, and high school grade 1. The policy, encapsulated in the slogan “Five million textbooks for five million students,” reflects high national expectations for individualized learning. In this policy context, Codle was developed as a representative platform that integrates AI technology into the high school curriculum, particularly in computer science. Codle was designed in alignment with the national curriculum and digital textbook guidelines and aims to reduce teacher workload, support personalized learning, and foster AI literacy.

Codle offers three main functions. First, the AI Quiz Generator automatically creates level-specific practice questions based on uploaded materials, easing teachers’ assessment preparation and providing students with preview or review quizzes. Second, the AI Tutor provides real-time feedback during coding exercises and problem-solving activities, acting as a personal assistant for students even in large classrooms. Third, the Course Recommendation feature analyzes quiz and task performance to assign personalized learning paths by categorizing students into advanced, intermediate, or foundational levels. Finally, the Learning Dashboard allows teachers to monitor students’ learning data and deliver individualized feedback and support. These functions support personalized learning across all stages of instruction—planning, execution, and assessment.

However, simply integrating new AI tools does not automatically lead to improved learning outcomes. Without appropriate instructional design, digital resources can introduce unnecessary cognitive confusion. Overwhelming information or poorly structured interfaces may overload students’ working memory, reducing learning efficiency. Thus, to maximize the impact of platforms like Codle, instructional strategies that align with human cognitive architecture are essential. This study applies Cognitive Load Theory [1] to develop an instructional model that integrates Codle’s AI features into traditional lesson phases (Introduction–Development–Conclusion), with the goal of regulating and reducing cognitive load. Furthermore, the model was piloted in an actual high school classroom and qualitatively analyzed based on students’ experiences to explore its educational impact and areas for improvement.

## 2. Literature Review

*Cognitive Load Theory (CLT)* posits that learners have limited working memory capacity and that effective instructional design must manage the

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cognitive demands placed on learners [2]. According to the theory, cognitive load can be classified into three types: intrinsic cognitive load, which arises from the complexity and inherent difficulty of the content; extraneous cognitive load, which results from poor instructional design such as disorganized information or unclear explanations; and germane cognitive load, which refers to the mental effort invested in processing, integrating, and constructing new knowledge (i.e., schema development).

Effective instructional design seeks to regulate these three types of cognitive load. Intrinsic load should be managed by matching the content difficulty to the learner's level and presenting it in sequenced steps. Extraneous load should be minimized by eliminating unnecessary information and optimizing how content is presented. Germane load should be enhanced by activating prior knowledge, encouraging self-explanation, and providing timely feedback. CLT has been widely validated through applications in multimedia learning and problem-solving education and is increasingly applied to e-learning and AI tutoring systems.

Meanwhile, recent studies have examined the impact of digital textbooks and AI tutors on learning. The Korean Ministry of Education has identified key functions for next-generation digital textbooks, including AI-based learning diagnostics and analysis, adaptive learning paths, and learner-centric interactive content. These functions have been implemented in platforms like Codle. Lee and Ahn [4] analyzed current AI education services and identified core technologies such as personalized learning, AI-based assessment and feedback, and learning data analytics. These are critical for managing cognitive load by adjusting task difficulty and delivering instant feedback.

AI-based intelligent tutoring systems have been shown to increase engagement and reduce learning delays by providing individualized, real-time assistance. In one large classroom application, students reported improved participation and reduced wait time as the AI tutor provided on-demand hints, much like a personal tutor. Furthermore, the Course Recommendation function helps assign tasks aligned with each student's performance level—enrichment for high-achievers and foundational support for struggling learners—thus mitigating inefficiencies from mismatched task difficulty.

In summary, although prior research demonstrates the utility of individual AI functions in educational contexts, few studies have integrated these functions into a comprehensive instructional model grounded in CLT. There is a notable lack of structured frameworks for how AI tools can be pedagogically deployed throughout lesson flow. This study addresses that gap by proposing and validating an integrated, theory-driven instructional model for AI-enhanced digital textbook usage.

## 3. Methodology

*Model Design* - This study designed an instructional model based on the AI digital textbook, structured to regulate cognitive load. The model follows the conventional three-phase instructional sequence of Introduction – Development – Conclusion, with core AI-based supportive functions mapped to each phase to manage intrinsic, extraneous, and germane cognitive load. The instructional plan utilizing the AIDT was designed as follows.

Table 1. Instructional plan

| Stage | Sequence | | Activity | AIDT Features for Student | AIDT Features for Teacher |
|---|---|---|---|---|---|
| **Introduction** | Opening the Lesson Motivation Activate Prior Knowledge | | Board | Real-time opinion sharing via discussion board | Checking the Live Collaboration Board |
| **Development** | Lesson 3. *Programming Application* | | Lesson Plan | | Monitor individual student progress |
| | [Connecting Concepts] The Value of Software Development | | Worksheet | Assistance with Worksheet Activities | |
| | Follow-along Example Learning | Learning by Following Examples | Python | AI Tutor: Worksheet Assistant | Note-taking for worksheet evaluation |
| | | Hands-on Practice: Learning by Following Examples | | **AI Tutor:** AI-Based Automated Evaluation of Algorithm Problems Support for Debugging Recommendations from a Personalized Question Bank | Real-time Python Monitoring |
| | | Applying Code Concepts | | | |
| | Inquiry-Based Learning: *Prime Number Checker Program* | Inquiry Activity: *Creating a Prime Number Checker Program* | Worksheet | **AI Tutor:**<br>- Worksheet Assistant<br>- Programming Process Assistance<br>- Debugging Feedback<br>-Feedback for Error Resolution | Note-taking for worksheet evaluation |
| | | Hands-on Practice: *Creating a Prime Number Checker Program* | Python | | **AI Teaching Assistant:** Real-Time Monitoring of Individual Learning Progress through the Dashboard |
| | | Assessment: *Creating a Prime* | | | **AI Teaching Assistant:** Assessment |

| Stage | Sequence | Activity | AIDT Features for Student | AIDT Features for Teacher |
|---|---|---|---|---|
| | *Number Checker Program* | | | for Learning, Real-time worksheet monitoring and AI-Powered Auto-Grading |
| | Learning Path Decision Point | Video | Personalized Learning by Achievement Level | Designing Individualized Learning Pathways(Pre-instructional) |
| Closure | Unit Summary (Student Self-Check) | Lesson Plan | Summary and Review | Viewing the Entire Class's Learning Activity Results for This Lesson via the Dashboard |
| | Unit Self-Assessment | Worksheet | Emotionally Supportive Feedback Provided by the AI Tutor | Delivering Personalized Feedback from Teachers through Direct Messaging |
| | Reflection and Consolidation After-school Review Check | Quiz | Study Room | Assigning Individual Tasks |
| Conclusion (Post-Lesson) | T : Post-Lesson Review and Data-Informed Instructional Design<br>S : AI-generated tasks, Teacher-assigned work, | Python | Achievement Board | - Reviewing the Lesson Summary<br>- Reflective Analysis through Dashboards; **Leaderboard** (teacher-facing dashboard) and the **Achievement Board** (student-facing dashboard)<br>- AI assistant ; Prescriptive Planning for the Next Lesson: |

### *Introduction Phase*

In the introduction phase, AI Digital textbook platform **AI Quiz Generator** is used to activate students' prior knowledge and enhance motivation. Teachers input core concepts or key summaries, and the system automatically generates personalized pre-lesson quizzes tailored to each learner's profile. These formative quizzes help students recall foundational knowledge while enabling teachers to quickly diagnose learners' prior understanding.

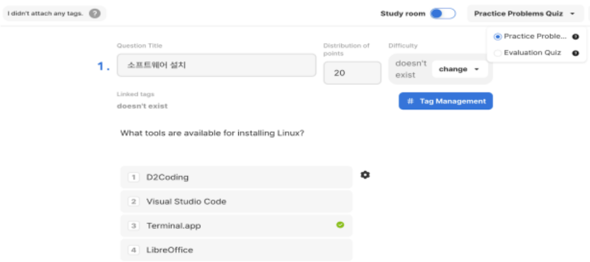


Figure 1. A quiz generated by AI

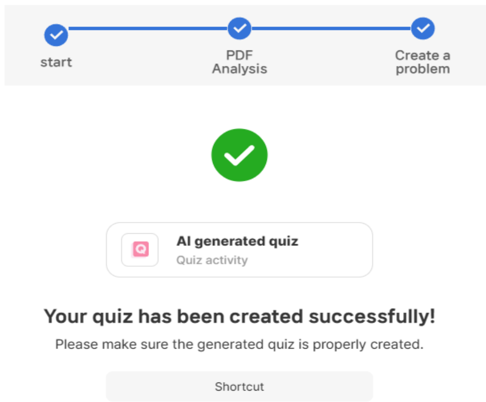


Figure 2. Create a review quiz with AI

Immediate AI-generated feedback allows students to recognize correct conceptions and identify misunderstandings, thereby reducing extraneous cognitive load caused by uncertainty or lack of preparation. In parallel, the board feature enables real-time opinion sharing, where students engage in brief discussions related to the topic, promoting active cognitive engagement.

Teachers may also monitor student contributions using the live collaboration board, supporting diagnostic insight at the outset of instruction. This enables CSCL (Computer-Supported Collaborative Learning) in computer science education [3]. These tools ensure that learners enter the lesson with activated schema and a clear cognitive focus on the learning objectives.

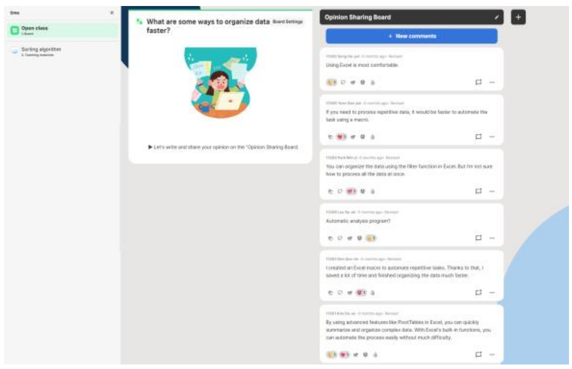


Figure 3. The live collaboration board

*Development Phase*

The development phase centers on personalized learning and adaptive scaffolding through Codle's AI Tutor, Course Recommendation system, and real-time monitoring dashboard.

During programming tasks, the AI Tutor provides real-time, context-sensitive feedback.

When learners encounter Python errors, the tutor offers natural language explanations and guides them step-by-step—not by giving direct answers, but through strategic hints that promote self-regulated problem-solving. This scaffolding minimizes unproductive struggle and encourages productive cognitive effort.

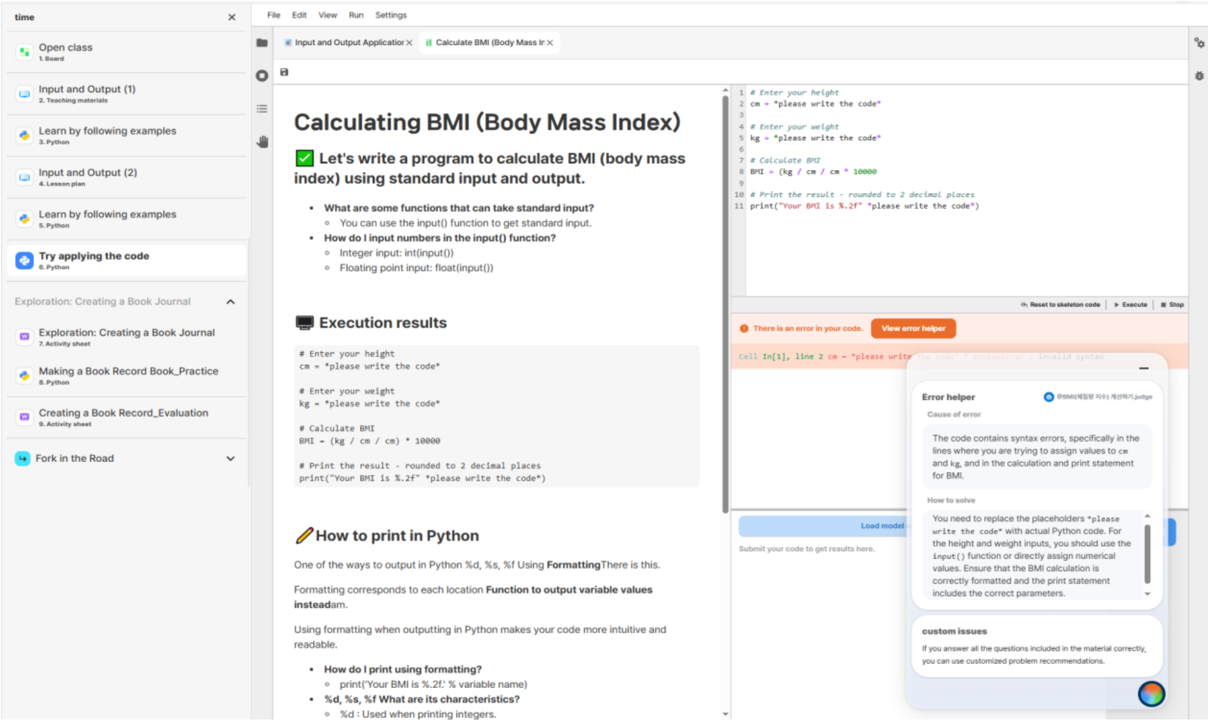


Figure 4. Error correction feedback of AI tutor

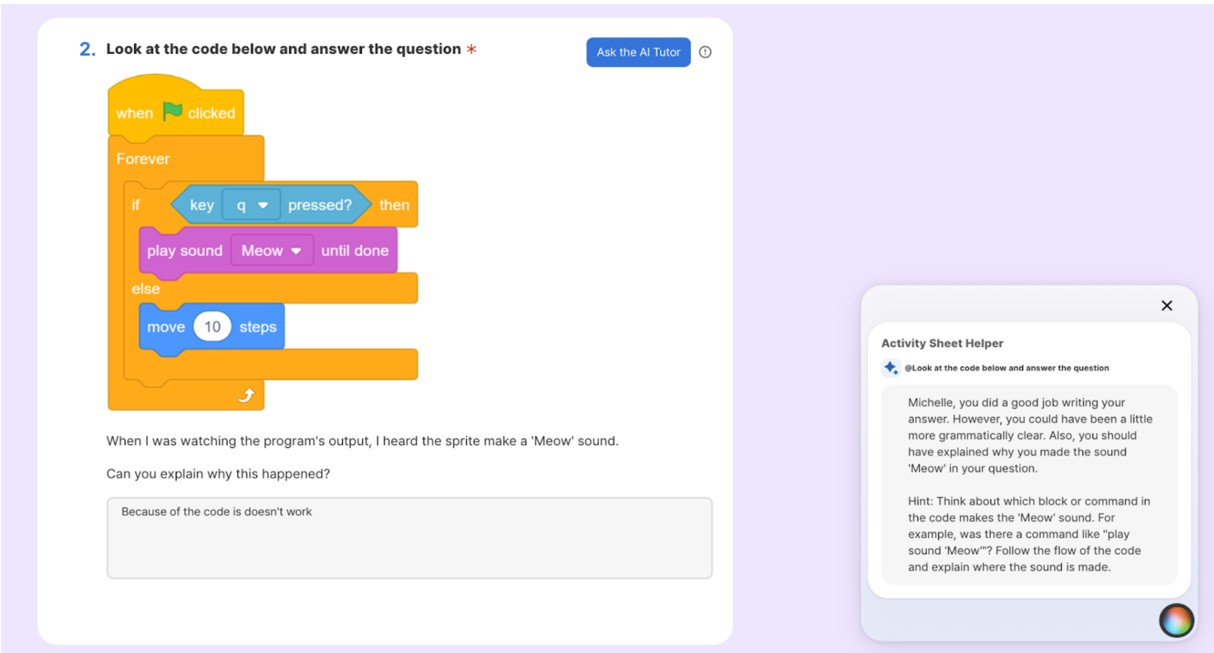


Figure 5. Real-time feedback in activity

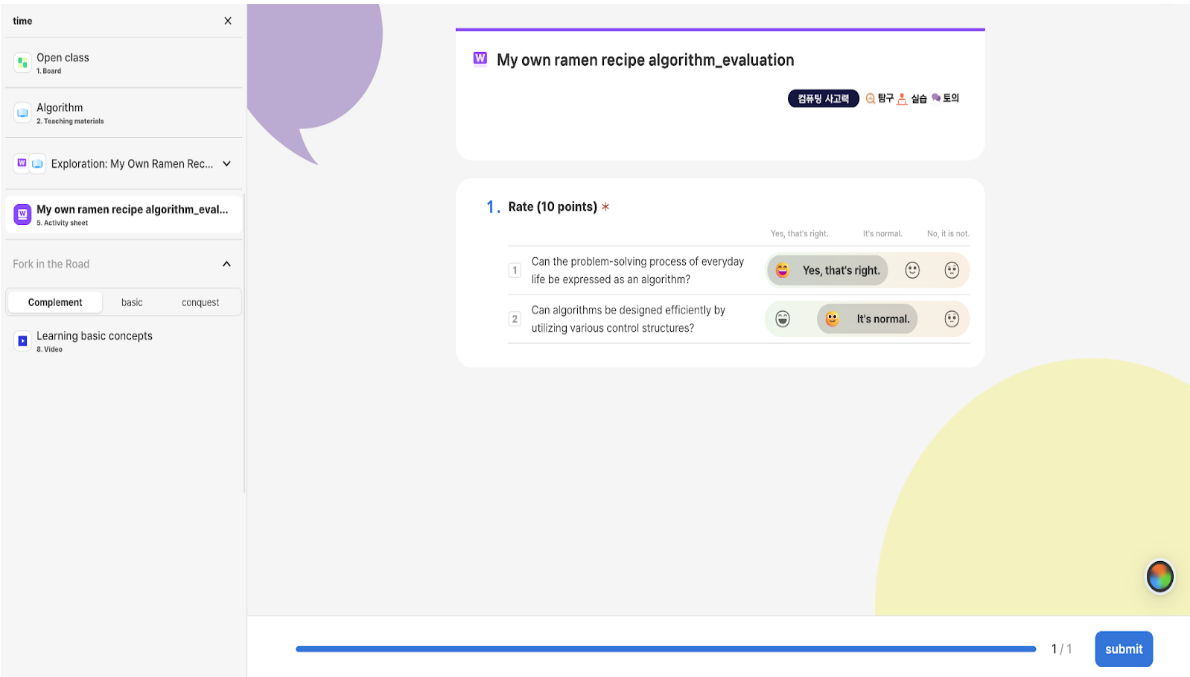


Figure 6. Course recommendation

Course recommendation engine analyzes real-time performance data to adaptively assign enrichment tasks for high-performing learners or supplementary materials (e.g., videos, concept reviews) for those who need more support.

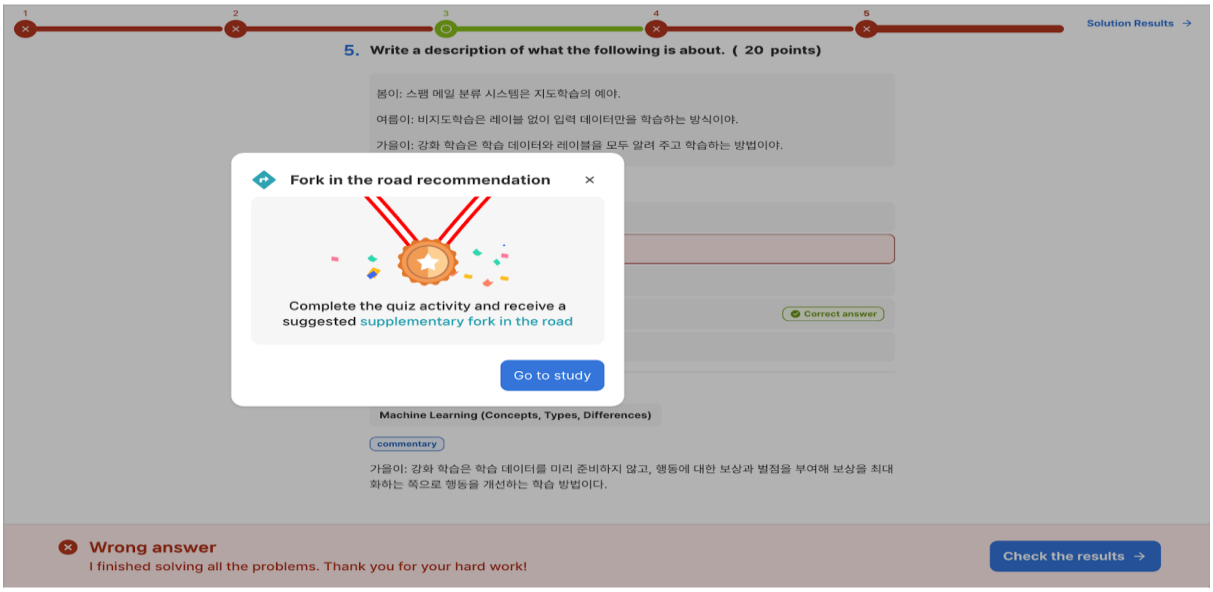


Figure 7. In-class foundational support for struggling learners

- Throughout this phase, the teacher-facing dashboard visualizes student progress (e.g., time-on-task, error frequency, completion rates), enabling data-informed decision-making and timely intervention. This adaptive structure helps maintain an optimal level of intrinsic load while avoiding both overload and disengagement, ensuring alignment between instructional goals and learner needs.

*Conclusion Phase*

In the conclusion phase, Codle supports reflection, consolidation, and forward planning through a combination of student and teacher tools.

- Students complete end-of-lesson quizzes, and any incorrect responses are compiled into their personalized "Study Room," where they can review, retry, and ultimately master the missed content—facilitating germane cognitive processing.
- Teachers access the learning dashboard to review class-wide and individual learning outcomes, enabling automated individualized feedback delivery. Through the Achievement Board (student-facing, teacher-facing) and Leaderboard (teacher-facing) dashboards, both learners and instructors visualize progress and achievements.

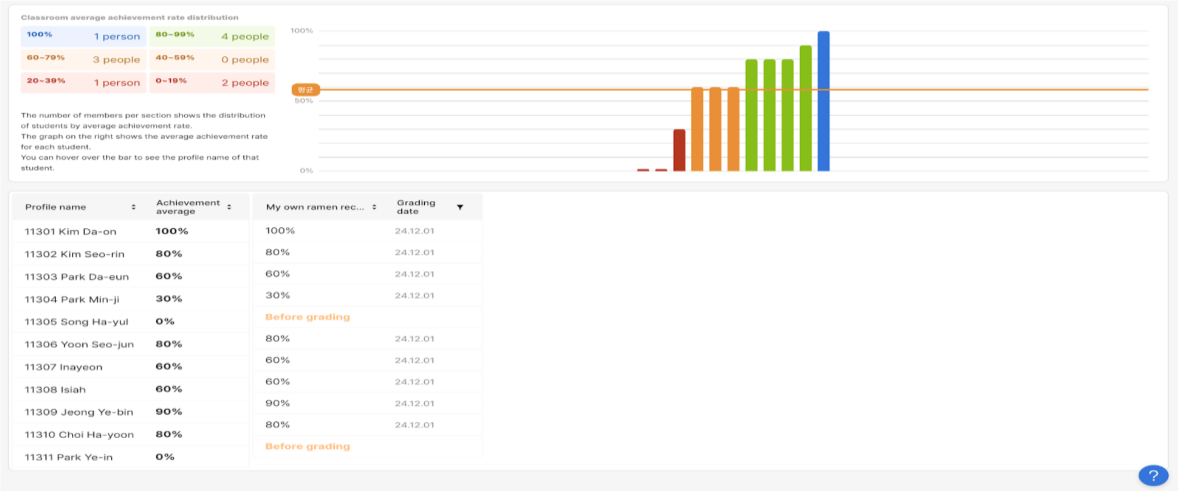


Figure 8. Leaderboard (teacher-facing)

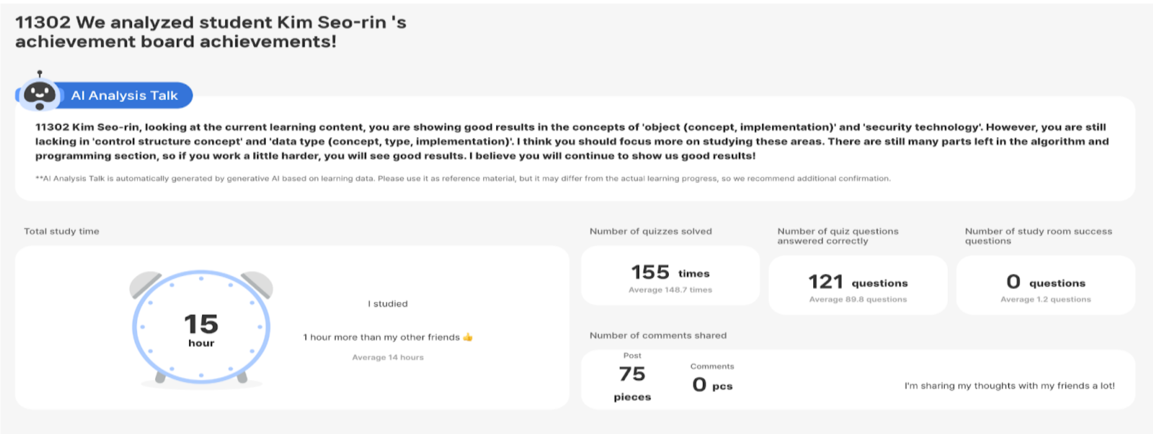


Figure 9. Achievement board
(student, teacher-facing)

- Finally, teachers engage in post-lesson instructional reflection using Codle's data insights, planning prescriptive pathways for future learning based on performance data. This includes assigning individual tasks and adjusting subsequent lessons to better meet student needs.

## 4. Results

Qualitative interview results revealed several positive effects of the Codle-based instructional model on students' cognitive load. Students' responses are summarized below according to the main Codle features used:

### 4.1. Experience with the AI Quiz Generator (Introduction Phase)

Students responded that the AI-generated quizzes given before class helped them better understand the lesson. One student shared:

*"By taking the quiz beforehand, I realized what I didn't know, so I was more focused during class."*

Another mentioned that the quiz sparked their curiosity, saying:

*"After getting the quiz right, I wanted to learn more in class."*

Overall, the pre-lesson quizzes contributed to increasing engagement and reducing the initial confusion often felt at the start of a lesson.

### 4.2. Experience with the AI Tutor (Development Phase)

Almost all students reported positive experiences with the AI Tutor. Particularly during coding exercises, students appreciated the real-time hints. One student remarked,

*"When error messages in English came up, the AI Tutor explained them in a way I could understand."*

Another said,

*"I fixed my mistake right away and moved on without wasting time*."

Students liked the fact that the AI Tutor encouraged them to think for themselves rather than giving direct answers. This support reduced cognitive frustration and increased self-efficacy.

### 4.3. Experience with Course Recommendation (Development Phase)

Students responded positively to the personalized tasks provided by Course Recommendation. High-performing students appreciated the challenging additional tasks, while those needing support were relieved to receive simpler explanations and review materials. While some students initially felt uncomfortable receiving different assignments from their peers, they soon understood the rationale. Most students reported increased focus and task immersion. One even described the experience as:

*"like playing a learning game."*

### 4.4. Experience with the Learning Dashboard and Review Activities (Conclusion Phase)

Students found it meaningful to visually check their learning progress and receive feedback through Codle's dashboard. They commented:

*"I could see exactly what I understood and what I didn't," and "It was fun, like checking a game scoreboard."*

Many used the AI explanations and teacher comments to review missed questions independently. One student said:

*"The content matched my level, so it felt doable,"*

indicating reduced burden and increased autonomy. While a few students expressed concern about seeing others' scores, most were not negatively affected.

### 4.5. Summary

Student interviews confirmed that the proposed instructional model has the following effects in terms of cognitive load:

- Reduction of extraneous cognitive load: Clear guidance and real-time hints minimized confusion and frustration.
- Adjustment of intrinsic cognitive load: Tasks were matched to students' levels, maintaining optimal cognitive effort.
- Promotion of germane cognitive load: Feedback-driven thinking, self-assessment, and increased autonomy encouraged deeper cognitive engagement.

These findings support the effectiveness of the Codle-based instructional model in enhancing learners' cognitive processing efficiency.

## 5. Discussion

The Codle-based instructional model proposed in this study is evaluated to have high theoretical validity from the perspective of cognitive load theory. First, the AI tutor's immediate feedback, AI quiz-driven pre-learning stimulation, and dashboard-based personalized feedback all contributed to reducing extraneous cognitive load. Students were able to stay engaged in learning by receiving clear guidance without confusion or unnecessary repetition.

In addition, Codle's level-based task recommendation feature adjusted to the learner's level without excessively increasing intrinsic cognitive load, thereby reducing the likelihood of task abandonment. This design helps minimize working memory overload and allows learners to focus on achievement.

Positive responses were also observed regarding germane cognitive load. Learners were encouraged to think through hints rather than simply being given the correct answers, and many were seen planning their own learning based on feedback even after class. This positively influenced schema formation and the activation of metacognitive strategies, contributing not only to cognitive growth but also to enhanced self-efficacy and affective attitudes.

This instructional model organically integrates AI technology while maintaining the traditional structure of classroom instruction (introduction–development–closure), showing high potential for application in educational settings. From the teacher's perspective, Codle's features reduce the burden of lesson preparation while enabling real-time diagnosis and feedback, thereby improving both feasibility and efficiency. For students, it has been shown to enhance engagement, a sense of challenge, and self-directed learning.

## 6. Conclusion

In conclusion, this study demonstrates that systematically integrating AI digital textbook features with Cognitive Load Theory across structured lesson phases can effectively optimize students' cognitive processing and learning engagement in high school computer science education. The Codle-based instructional model shows that AI tools—when guided by sound learning theory—can support adaptive scaffolding, self-regulated learning, and teacher efficiency without disrupting traditional classroom practices. By extending the applicability of Cognitive Load Theory to AI-enhanced learning environments, this research offers a theoretically grounded and practically replicable framework for the effective pedagogical use of AI digital textbooks. As educational systems increasingly adopt AI-driven technologies, such theory-informed instructional designs will be essential to ensure meaningful and sustainable improvements in teaching and learning.

## 7. Future Works

Reliability of AI Feedback: Some hints were found to be inaccurate, indicating the need for teacher monitoring and correction. Future improvements in the AI model and the design of teacher-platform collaboration are necessary.

Teacher Workload: Initial time investment is required for reviewing and grading open-ended tasks, dashboard use, and real-time monitoring. Teacher training and improvements in usability are essential.

Technological Accessibility: Availability of devices and network conditions can affect instructional effectiveness. Efforts to improve infrastructure and support students' digital literacy are required.

Future Research Suggestions: Follow-up studies should include controlled experiments and expanded applications across various subjects and grade levels for deeper exploration.

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