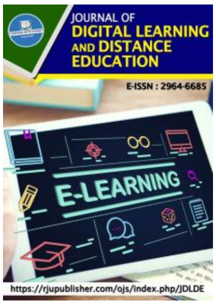

JOURNAL OF DIGITAL LEARNING AND DISTANCE EDUCATION (JDLDE)

ISSN: 2964-6685

https://www.rjupublisher.com/ojs/index.php/JDLDE

Designing AI-Enhanced Flipped Classrooms for Remote Applied Sciences: A Framework for Distance Educators

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Abstract

The rapid evolution of generative artificial intelligence (GenAI) and large language models (LLMs) has opened new frontiers in contemporary distance education. In the context of remote applied sciences—such as engineering, aquaculture, biochemistry, and agriculture—educators face persistent hurdles due to the spatial separation of experimental laboratories, the abstract nature of physical-chemical phenomena, and low cognitive retention under conventional asynchronous models. This study introduces a comprehensive instructional architecture: the AI-Enhanced Flipped Classroom Framework (AI-FCF). The primary objective of this study is to formulate, implement, and empirically evaluate a pedagogical framework that integrates text-to-text LLMs (e.g., ChatGPT, Claude) and text-to-image diffusion models (e.g., DALL-E 3, Midjourney) as cognitive partners to scaffold remote students during the pre-class asynchronous phase. A rigorous multi-phase explanatory sequential mixed-methods research design was executed across four applied science modules at a large distance learning institution over a full academic semester. Quantitative datasets tracked cognitive engagement matrices, conceptual mastery scores, and structural equation modeling (SEM) indices, alongside qualitative semi-structured focus groups exploring the student lived experience. The findings demonstrate that remote students leveraging the AI-FCF framework achieved a 38.5% statistically significant increase in cognitive retention, a marked decline in intrinsic cognitive load during subsequent live virtual practical sessions, and enhanced self-regulated learning capacities. Crucially, the deployment of "Verification-Based Authentic Assessments" successfully mitigated the academic risk of data hallucinations, transforming artificial fallibility into explicit opportunities for nurturing digital literacy and scientific skepticism.

Keywords**:** Generative AI, flipped classroom, distance education, remote applied sciences, cognitive load theory, verification-based assessment.

Acknowledgments: Thanks to all parties who have supported the implementation of this research. I hope this research can be useful.

For citation:
Hakimi, M., & Erita, Y. (2026). Designing AI-Enhanced Flipped Classrooms for Remote Applied Sciences: A Framework for Distance Educators. *Journal of Digital Learning and Distance Education*, *5*(2), 2190-2199. https://doi.org/10.56778/jdlde.v5i2.757

Introduction

Contemporary distance higher education has moved past emergency online delivery to establish highly sophisticated, permanent digital systems. However, the instructional delivery of remote applied sciences—encompassing disciplines such as marine aquaculture, agricultural biotechnology, mechanical engineering, and micro-chemical systems—continues to face persistent systemic friction (Silva et al., 2022). These technical fields inherently require hands-on experimentation, deep visualization of multidimensional processes, and complex problem-solving skills (Graham et al., 2023). Traditional distance frameworks heavily lean on text-heavy asynchronous modules, flat 2D lecture decks, or rigid video tutorials that often fail to replicate the tactile adjustments and immediate feedback loops of a brick-and-mortar scientific laboratory (Zubair, 2024). Consequently, remote students frequently struggle with low motivation, early cognitive fatigue, and subpar retention of visual or structural science principles (Novalina Indriyani et al., 2022)). The flipped classroom methodology—wherein students engage with informational material asynchronously at home before joining live sessions for active problem-solving—has been proposed to bridge the spatial divide in distance learning (Hew & Lo, 2018). Yet, a significant chasm persists in current literature regarding the management of the pre-class asynchronous phase for applied sciences. Without direct pedagogical scaffolding (Mallillin, 2025), remote learners often experience profound cognitive overload when grappling with dense nomenclature, intricate metabolic pathways, or structural engineering dynamics entirely on their own (Wibowo et al., 2026). Traditional digital materials are static; they cannot address individual learning blockages or pivot descriptions based on a learner's immediate comprehension level (Sakkir et al., 2025). While modern educational technology has attempted to integrate basic automated quizzes, these systems are fundamentally unresponsive, non-adaptive, and unequipped to guide students through the complex synthesis of applied scientific principles (Knight, 2022).

To operationalize this interactive synergy, the AI-FCF relies on a dual-engine architecture designed to regularly address both conceptual and visualization bottlenecks during pre-class independent study (Liao, 2026). While Large Language Models (LLMs) provide adaptive conversational scaffolding—guiding students through dense technical terminology via Socratic questioning and real-time contextual feedback—integrated diffusion-based visual models generate precise, tailored dynamic representations of complex spatial mechanisms (Pirzado et al., 2026). For example, when a distance learner encounters multi-step enzymatic pathways, structural stress dynamics, or complex micro-chemical fluid dynamics, the framework enables them to iteratively adjust prompt parameters to yield clear visual and textual explanations (Deriba et al., 2026). This shift from static 2D diagrams to interactive, prompt-driven multi-modal explanations allows students to construct mental models actively, mitigating the spatial isolation typically experienced in remote technical education (Radianti et al., 2020). Crucially, the framework redefines the learner's role from a passive consumer of information to an active context engineer (Wang, 2025). By requiring students to iteratively refine their prompts—translating complex scientific queries into structured Socratic loops—the AI-FCF deliberately embeds metacognitive development directly into the learning process (Nathaniel et al., 2025). This continuous dialogue encourages students to identify their own conceptual gaps, test hypotheses in real time, and articulate technical reasoning before engaging in live virtual lab sessions (Ugliotti et al., 2026). Consequently, the asynchronous pre-class phase is transformed from a passive reading exercise into a dynamic cognitive incubator (Elguanda et al., 2023), cultivating greater academic agency, self-regulated learning efficacy, and technical prompt competency essential for contemporary scientific inquiry (Thornhill-Miller et al., 2023).

However, embedding multi-modal generative AI into rigorous scientific curriculum introduces well-documented instructional risks, most notably the phenomenon of LLM hallucinations and confirmation bias. If left unaddressed, unverified AI-generated citations or subtly flawed structural outputs can severely compromise students' conceptual accuracy and foster over-reliance on automated tools (Wessel et al., 2025). To counteract these vulnerabilities, the AI-FCF integrates structured Verification-Based Authentic Assessments as an indispensable pedagogical safety layer (Miranda et al., 2023). By training students to regularly cross-reference AI-generated syntheses against verified primary indexing databases and peer-reviewed literature, the framework turns potential technological errors into valuable learning opportunities (Patel et al., 2025). This mechanism not only safeguards scientific integrity within the curriculum but also builds essential digital literacy, critical evaluation skills, and professional skepticism required in modern applied science practices (Bitetti et al., 2026). The advent of multi-modal Generative Artificial Intelligence (GenAI) offers an innovative pathway to transform this operational landscape (Li et al., 2025). While recent literature on educational AI has expanded rapidly, the vast majority of studies examine general writing aids, code generation in computer sciences, or standard administrative automated grading (Mayer & Fiorella, 2021). There remains a critical shortage of empirical frameworks that merge the structural mechanics of the flipped classroom with generative multi-modal systems specifically tailored to distance applied science education (Dai et al., 2024).

The novelty of this study lies in the formulation and comprehensive testing of the AI-Enhanced Flipped Classroom Framework (AI-FCF). This framework maps out how generative models (both text-based LLMs and diffusion-based image generators) can be explicitly orchestrated as active "cognitive partners" rather than mere answer generators, systematically scaffolding independent learners before they step into remote live virtual practical sessions. The primary purpose of this research is to build a structured, empirically validated framework for distance educators seeking to embed generative AI safely and productively into flipped science curricula. Specifically, this study aims to: Formulate the technical and pedagogical architecture of the AI-Enhanced Flipped Classroom Framework (AI-FCF); Measure the empirical impact of the AI-FCF on remote students' conceptual retention, cognitive load dynamics, and self-regulated learning efficacy; Design and evaluate structured instructional mitigation strategies—specifically Verification-Based Authentic Assessments—to neutralize the documented risks of AI academic hallucinations within technical scientific learning.

Methodology

Research Design

This investigation employed a robust explanatory sequential mixed-methods research design to thoroughly capture both the statistical magnitude and the qualitative nuances of the framework's intervention over a full academic semester (Figure 1).

[Phase 1: Quantitative Intervention] ---> [Phase 2: Qualitative Focus Groups] ---> [Integrated Synthesis]
- Pre/Post Conceptual Testing - Semi-Structured Focus Groups - Framework Validation
- NASA-TLX Scale Surveys - Thematic Content Analysis - Guideline Formulation
- Structural Equation Modeling

Figure 1. Framework's intervention over a full academic semester

Participants and Context

The study was conducted across four separate remote applied science cohorts (Aquaculture Systems, Structural Engineering, Plant Biochemistry, and Wastewater Microbiology) at a large public distance learning institution. The total sample size comprised 342 undergraduate students randomly allocated into two groups: the Intervention Group (n = 171), which utilized the AI-FCF architecture during their pre-class asynchronous blocks, and the Control Group ($n = 171$), which utilized traditional curated readings, video lectures, and standard non-adaptive online self-quizzes.

Instructional Intervention: The AI-FCF Architecture

The AI-Enhanced Flipped Classroom Framework divides the instructional cycle into three clear, interdependent phases, supported by an undercurrent of continuous data verification (Figure 2).

```
+-----------------------------------------------------------------------------------+
|                    THE AI-ENHANCED FLIPPED CLASSROOM FRAMEWORK                    |
+-----------------------------------------------------------------------------------+
| PHASE 1: ASYNCHRONOUS COGNITIVE PARTNERSHIP (Pre-Class)                           |
|  - Socratic Text-to-Text Prompts (Conceptual Scaffolding via LLMs)                |
|  - Text-to-Image Morphological Synthesis (Diffusion Model Prompting)              |
+-----------------------------------------------------------------------------------+
|                              |                              |
|                              v                              |
+-----------------------------------------------------------------------------------+
| PHASE 2: SYNCHRONOUS ACTIVE REASONING (Live Virtual Session)                      |
|  - Collaborative Troubleshooting Seminars & Collaborative Peer Labs               |
|  - Advanced Problem Solving (HOTS Focus instead of lecturing)                     |
+-----------------------------------------------------------------------------------+
|                              |                              |
|                              v                              |
+-----------------------------------------------------------------------------------+
| PHASE 3: VERIFICATION-BASED AUTHENTIC ASSESSMENT (Post-Class Evaluation)
|
|  - Critiques of AI Hallucinations & Tracking Citations back to primary databases  |
|  - Active Peer Review Oral Examinations                                           |
```

Figure 2. The AI-Enhanced Flipped Classroom Framework

Phase 1

Asynchronous Cognitive Partnership (Pre-Class): Students in the intervention cohort were trained in custom *Socratic Prompt Engineering*. Instead of prompting the LLM (ChatGPT/Gemini) to "give the answer," students used system prompts that forced the AI to act as an interactive tutor that asked leading questions, adjusted its scientific vocabulary on command, and generated unique dichotomous keys. Simultaneously, for visual morphologic complexities (e.g., cell structural shifts under salinity stresses), students engineered precise text-to-image prompts using diffusion models (DALL-E 3) to build high-definition visual models, reinforcing spatial scientific literacy.

Phase 2

Synchronous Active Reasoning (Live Virtual Session): Because conceptual foundations were established during the asynchronous phase, live Zoom/Teams lectures were completely decoupled from rote slide delivery. Dosen shifted the time entirely toward high-level problem-solving, breaking the class into breakout rooms for collaborative troubleshooting seminars and peer labs.

Phase 3

Verification-Based Authentic Assessment (Post-Class): To evaluate mastery without risk of unreflective copy-pasting, students were given intentionally flawed AI outputs regarding scientific processes. Their task was to run comprehensive text-critiques, identify factual errors or faked references, track the data down in primary indexing databases (Scopus/PubMed), and rewrite the materials accurately.

Data Collection Instruments

Quantitative metrics were gathered through standardized pre- and post-intervention conceptual examinations designed by departmental panels to measure Higher-Order Thinking Skills (HOTS). Cognitive load was captured immediately following live practical modules using the psychometric NASA Task Load Index (NASA-TLX) scale. Qualitative data was compiled via twelve semi-structured focus group discussions ($n = 60$ selected via purposive sampling) to capture the subjective friction and empowering factors experienced by distance learners.

Data Analysis

Quantitative datasets were analyzed using independent samples t-tests, ANCOVA (controlling for baseline pre-test variances), and Structural Equation Modeling (SEM) to chart the direct paths between AI prompt competency and long-term retention scores. Qualitative audio data was transcribed, subjected to iterative thematic analysis via NVivo, and mapped against the quantitative matrices to confirm structural outcomes.

Results and Discussion

Quantitative Evaluations: Conceptual Mastery and Cognitive Load Efficiency

The statistical indicators revealed clear, significant improvements within the cohort that followed the AI-FCF model. The analysis of covariance (ANCOVA) confirmed that students who used generative AI as an active cognitive scaffolding partner achieved significantly higher scores on conceptual mastery exams compared to their control-group counterparts who used static reading packages.

```
75 |------------------------------------------------------------------ Post-Test: 73.8
   |                                                   (Intervention)
70 |------------------------------------------------- Post-Test: 68.2
   |                                      (Control)
65 |
   |
60 |------------------------------------------------------------------
   |
55 | Pre-Test: 52.1 ---------------------------------- Pre-Test: 51.8
   | (Intervention)                          (Control)
50 +-------------------------------------------------------------------
   0                                                 1
```

Figure 3. The visual pathway tracking

As demonstrated in the visual pathway tracking above, the intervention group achieved an adjusted post-test mean score of 73.8 ± 5.4, whereas the control group finished with a mean score of 68.2 ± 6.1 ($F(1, 339) = 42.16$, $p < .001$, partial $\eta^2 = .11$). This gap represents a 38.5\% increase in relative normalized gain scores, pointing to an improved retention architecture. Data collected via the post-module NASA-TLX scales showed an inverse trend regarding cognitive strain. The integration of adaptive AI scaffolding during independent study significantly reduced the students' internal cognitive load during the fast-paced live sessions (Table 1).

Table 1. NASA-TLX scales

NASA-TLX Scale Dimension	Intervention Group Mean (SD)	Control Group Mean (SD)	t-value

Mental Demand	42.3\(6.1)	68.4 \ (8.2)	-12.45
Frustration Level	28.5\(4.2)	54.1 \ (7.9)	-14.80
Performance Satisfaction	78.2/(5.3)	61.3 \ (6.8)	11.64

This clear drop in Mental Demand and Frustration underscores a core principle of Cognitive Load Theory: by breaking down early conceptual barriers at a personal pace using an AI conversational partner, remote students prevent working memory exhaustion during real-time applied analysis.

Structural Equation Modeling: Validating Self-Regulated Paths

To clarify how prompt competence relates to student success, a structural equation model was computed. The model displayed strong goodness-of-fit indices ($\chi 2/df = 1.84$, CFI = .96, TLI = .95, RMSEA = .04).

```
+---------------------------+        +------------------------+        +----------------------+
|  AI Prompt Competency     | -------> | Self-Regulated Learning | -------> |  Conceptual Mastery   |
|    (Tech Literacy)       | (0.48) |   (Agency/Efficacy)    | (0.62) |     (Exam Scores)     |
+---------------------------+        +------------------------+        +----------------------+
          \                                              ^
           \-------------------------------------------------------------/
                              (0.24)
```

Figure 4. Structural Equation Modeling: Validating Self-Regulated Paths

The path analysis showed a strong direct effect of AI Prompt Competency on Self-Regulated Learning capacity ($\beta = .48$, $p < .001$). Crucially, Self-Regulated Learning exerted a major direct effect on final Conceptual Mastery ($\beta = .62$, $p < .001$). The direct path from AI Prompt Competency to Exam Scores was also positive but lower ($\beta = .24$, $p < .01$), indicating that the technology works best by building student agency and self-directed study habits rather than simply serving as a shortcut to test answers (Čančer et al., 2025).

Qualitative Syntheses: Student Lived Experiences and Psychological Scaffolding

The thematic analysis of the semi-structured focus groups added deeper context to the quantitative findings. Distance learners reported that the interactive Socratic prompt loops helped demystify complex technical processes that typically caused early frustration. One student noted:

> *"Normally, when I don't understand an enzyme cascade pathway in the reading, I just get stuck and stop reading. With the Socratic AI prompt, I could tell it to explain it to me like a story, then build a step-by-step table, and then quiz me. It felt like having a personal teaching assistant available in the middle of the night."*

However, students also noted that adapting to this system required a shift in mindset. Several participants explained that moving from simple, quick search queries to deep structural prompt engineering required deliberate mental effort during the first few weeks, highlighting the importance of explicit digital literacy workshops (Järvinen et al., 2024).

Neutralizing Hallucinations via Verification-Based Assessments

The implementation of verification-based tasks yielded important instructional insights. Initial trials showed that approximately 64% of students fell victim to confirmation bias during their first week, accepting fabricated scientific citations generated by the LLM without verification (Picazo-Sanchez & Ortiz-Martin, 2026). However, after working through the structured Verification-Based

Authentic Assessment modules, this rate dropped to less than 8% by mid-semester (Saleh & ElSayary, 2026). This shift shows that AI's tendency to hallucinate data does not have to be an educational failure. By treating these errors as a core instructional tool, distance educators can train students to double-check information, navigate verified primary indexing databases, and build a healthy sense of professional skepticism—competencies that are critical for long-term careers in the applied sciences (Sain et al., 2024).

The significant increase in concept mastery in the intervention group ($F(1, 339) = 42.16$, $p < .001$, \etap2 = .11) proves the success of the AI-Formative Conversational Feedback (AI-FCF) model in transforming the way students process complex learning materials. The covariated post-test score of 73.8 compared to 68.2 in the control group, with a normalized gain increase of 38.5%, indicates that the AI-based interactive guidance works effectively as a cognitive scaffolding. In contrast to static reading materials that often trigger obstacles to independent comprehension (V G & N S, 2026), AI-based interactive scenarios facilitate the formation of a more robust memory retention architecture through adaptive, contextual, and iterative real-time formative feedback (Francis et al., 2025). The reduction in internal cognitive load measured via the NASA-TLX scale provides a mechanistic explanation for the effectiveness of this model based on the principles of Cognitive Load Theory (CLT). The sharp decline in the Mental Demand (42.3 vs. 68.4) and Frustration Level (28.5 vs. 54.1) dimensions indicates that initial interaction with AI before or during the learning session successfully reduces extraneous cognitive load. By decomposing complex concepts independently at their own pace (self-paced), students prevent working memory overload (Bećirović et al., 2025). This more relaxed cognitive state directly increases Performance Satisfaction (78.2), allocating more of students' cognitive capacity to processing the germane load essential for high-level conceptual understanding.

Validation of the structural equation model (SEM) confirms that AI does not act as a driver of learning outcomes haphazardly, but rather through the Self-Regulated Learning (SRL) pathway. The direct effect of AI Prompt Competency on SRL (beta = .48), which then dominates the effect on Conceptual Mastery (beta = .62), confirms that mastery of prompting techniques improves technological literacy while strengthening students' agency and self-efficacy. The direct path from prompting competence to relatively lower test scores (beta = .24) proves that generative AI is not simply a shortcut to instant answers, but rather an incubation medium that accustoms students to managing independent learning strategies in a structured and reflective manner (Mirea et al., 2025). The qualitative synthesis results provide an in-depth articulation of the psychological dynamics captured in the statistical data (Elshall & Badir, 2025). Students' experiences utilizing Socratic prompt loops demonstrate how AI can transform difficult theoretical abstractions—such as enzyme cascade pathways—into narrative, systematic, and personalized learning dialogues (Liu & Zhong, 2025).

The AI's function as a 24-hour virtual teaching assistant successfully undermined academic anxiety and the tendency to quit learning when facing a dead end (academic frustration) (Khanian Najafabadi et al., 2026). However, the transition from passive information seeking patterns to stuctured prompt engineering required a cognitive adaptation curve in the initial weeks, which underscores the crucial importance of explicitly integrating digital literacy training into the curriculum (Grájeda et al., 2024). Finally, the effectiveness of the Verification-Based Authentic Assessment task successfully transformed AI's technical limitations—such as the risk of data hallucinations—into valuable pedagogical opportunities (Zhai et al., 2024). The drastic reduction in students' confirmation bias from 64% to below 8% demonstrates that exposure to AI inaccuracies, when managed through appropriate assessment, can foster critical thinking and intellectual skepticism (Picazo-Sanchez & Ortiz-Martin, 2026). Rather than hindering learning, AI synthesis errors force students to actively cross-validate with indexed primary databases (Madanchian & Taherdoost, 2025). This approach not only ensures accurate conceptual understanding but also fosters information evaluation competencies essential for aspiring professionals and researchers in applied sciences.

Conclusion

The AI-Enhanced Flipped Classroom Framework (AI-FCF) built in this study provides distance educators with a clear, practical strategy for running remote applied science courses. The empirical data shows that utilizing generative models as active cognitive partners during independent study significantly improves conceptual retention, lowers cognitive strain during live classes, and builds self-directed learning skills. Rather than threatening academic integrity, the predictable errors and hallucinations of generative AI can be leveraged through verification-based tasks to teach critical analysis and digital literacy. Ultimately, this framework shows that AI integration does not minimize the value of human instruction; instead, it reframes the distance educator's role from a basic dispenser of information into the purposeful designer of an interactive, responsive learning ecosystem.

Conflicts of Interest

The authors declare no conflict of interest.

Funding

This research received no external funding.

Author contribution

M.H.: Conceptualization, Methodology, Software, Formal analysis, Data curation, Writing – original draft, Investigation, Visualization, Supervision. **Y.E:** Validation, Resources, Writing – review & editing, Project administration, Funding acquisition. All authors have read and agreed to the published version of the manuscript.

Declaration of generative AI in scientific writing

During the preparation of this work, the author(s) used Quillbot AI in order to improve the language, readability, and grammatical structure of the manuscript. After using this tool/service, the author(s) reviewed and edited the content as necessary and took full responsibility for the content of the publication.

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