DIGITAL TECHNOLOGY APPLICATION IN TEACHING CONSTRUCTION MATERIALS AT THE UNIVERSITY OF DANANG - UNIVERSITY OF TECHNOLOGY AND EDUCATION

ỨNG DỤNG CÔNG NGHỆ SỐ TRONG GIẢNG DẠY HỌC PHẦN VẬT LIỆU XÂY DỰNG TẠI TRƯỜNG ĐẠI HỌC SƯ PHẠM KỸ THUẬT - ĐẠI HỌC ĐÀ NẴNG

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Abstract - This article examines digital technology (DT) application in teaching the Construction Materials (CM) course at The University of Danang - University of Technology and Education (UD-UTE). A flipped classroom (FC) model was deployed on a Moodle Learning Management System (LMS), integrating digital tools (DT) like Gemini and NotebookLM to design instructional materials (IM) and establish a digital pedagogical (DP) space. By analyzing LMS data through correlation matrices and heatmaps, instructors evaluated students' self-regulated learning (SRL) to implement early warning systems. Results showed significant performance improvements over traditional methods, achieving a 93% pass rate (up from 75%) and a 6.52 average score (up from 5.5). However, surveys revealed first-year students' psychological barriers and a preference for traditional classrooms. The study recommends strengthening SRL, optimizing assessment alignment to reduce cognitive overload, and balancing face-to-face interaction with technology.

Key words - Construction materials; digital tools; flipped classroom; instructional materials; digital pedagogy

Tóm tắt - Bài báo nghiên cứu ứng dụng công nghệ số trong giảng dạy môn Vật liệu Xây dựng tại Trường Đại học Sư phạm Kỹ thuật - Đại học Đà Nẵng. Mô hình lớp học đảo ngược đã được triển khai trên Hệ thống Quản lý Học tập Moodle, tích hợp các công cụ số như Gemini và NotebookLM thiết kế tài liệu giảng dạy và không gian sư phạm số. Thông qua việc phân tích dữ liệu LMS bằng ma trận tương quan và bản đồ nhiệt, đã đánh giá năng lực tự học của sinh viên để đưa ra cảnh báo sớm. Kết quả cho thấy sự cải thiện về thành tích học tập so với các phương pháp truyền thống, tỷ lệ qua môn 93% (tăng từ 75%) và điểm trung bình 6.52 (tăng từ 5.5). Các khảo sát cũng chỉ ra những rào cản tâm lý của sinh viên năm nhất và xu hướng vẫn thích các lớp học truyền thống. Nghiên cứu khuyến nghị cần tăng cường năng lực tự học, đồng bộ hóa đánh giá nhằm giảm tải nhận thức và cân bằng tương tác trực tiếp với sử dụng công nghệ.

Từ khóa - Vật liệu xây dựng; công cụ số; lớp học đảo ngược; tài liệu giảng dạy; sư phạm số

1. Introduction

The rapid development of Education 4.0 has accelerated the integration of DT into higher education, transforming traditional teaching into more flexible, interactive, and learner-centered approaches. DT provides the foundation for creating, delivering, managing, and analyzing digital learning resources, enabling innovative teaching and learning environments [1]. Among these innovations, the FC has been widely implemented across higher education settings. In this approach, students study IM before class, while classroom time is devoted to discussion, collaborative learning, and practical problem-solving to promote deeper understanding [2, 3].

To support these instructional models, higher education institutions have increasingly adopted LMS, cloud-based learning resources, interactive educational software, and Artificial Intelligence (AI) technologies [4]. These technologies not only improve access to learning materials and learning flexibility but also generate valuable learning data. In particular, Learning Analytics based on LMS job-log data enables instructors to monitor students' learning behaviors, identify learning patterns, detect students at risk of poor performance, and provide timely instructional interventions [5]. Furthermore, DT and AI have expanded opportunities for continuous assessment, personalized learning, and competency-based evaluation, making assessment more flexible and data-driven than traditional examination-oriented approaches [6, 7]. The successful implementation of these technologies, however, also depends on appropriate institutional strategies, technological infrastructure, and the digital competencies of both instructors and students [8, 9]. However, the rapid proliferation of DT introduces critical challenges to academic integrity. Emerging literature suggests that learners may increasingly leverage AI tools to bypass independent critical thinking tasks, potentially fostering an over-reliance on automated outputs and eroding meaningful student-instructor interactions [10]. Consequently, educational institutions must establish appropriate pedagogical configurations and develop robust assessment methodologies to effectively govern human-AI collaboration in the learning environment [11].

Despite these advances, several challenges remain in applying DT to engineering education. In many technical courses, IM are still provided mainly as static digital documents or recorded lectures with limited interaction, reducing opportunities for active learning. Likewise, student assessment continues to rely primarily on attendance, mid-term examinations, and final examinations, providing limited evidence of students' learning processes, engagement, and SRL. These challenges are particularly evident in the CM course, which is a fundamental subject in civil engineering education. The course contains extensive theoretical knowledge, complex engineering concepts, and numerous technical standards that require students to integrate conceptual understanding with practical applications. Despite extensive individual research on FC, LMS, AI, and learning analytics, few studies have integrated these technologies into a dedicated digital framework for teaching CM. In particular, few studies have combined the development of interactive IM using AI with the analysis of LMS job-log data to evaluate students' learning engagement and SRL.

To address this research gap, this study establishes a DP space for the CM course by integrating DT into the FC model on the LMS platform. The research aims to achieve two primary objectives: (1) to develop interactive digital IM utilizing tools such as Gemini, NotebookLM, and Canva to facilitate students' self-directed learning; and (2) to analyze job-log data on the LMS using correlation analysis techniques and heatmaps to evaluate student learning behaviors and engagement levels. The findings demonstrate the applicability of DT in creating interactive digital resources, while concurrently supporting data-driven instruction and assessment for the CM course.

2. Pedagogical implementation

2.1. Research context and subject matter

CM is a foundational course within the civil engineering curriculum, focusing on the fundamental characteristics, mechanical properties, quality assessment methodologies, and technical specifications of standard construction components. This two-credit course, comprising eight distinct chapters, is delivered to first-year civil engineering undergraduates at the UTE-UD. The course is supported by a published textbook aligned with the official syllabus; this resource facilitates independent study through integrated theoretical inquiries and practical exercises at the conclusion of each chapter, allowing students to focus on core learning objectives.

2.2. Pedagogical framework

The FC has been implemented by the instructor in teaching the CM course [12], and can be considered an appropriate pedagogical approach to support digital transformation in the context of Education 4.0 through the UTE-UD's LMS.

Intentional instructional material design serves as the core foundation of the DP space. This space (Figure 1) was developed on Moodle, an open-source LMS platform that has been officially adopted by the university since 2020. Within this environment, the instructor integrated various DT (Table 1) to design digital learning resources (Figure 2, Table 2) and organize learning activities based on the FC model. This approach enhanced learner interaction, supported personalized learning, and improved students' knowledge acquisition.

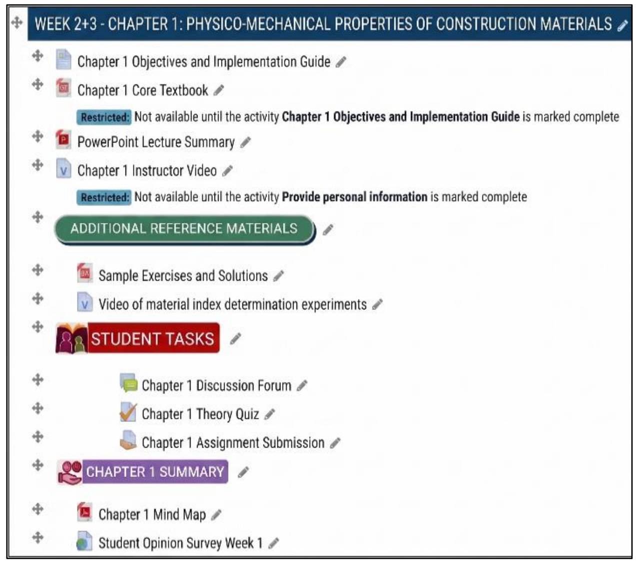

Figure 1. *Representative interface of the DP space designed on the LMS*

Table 1. *Summary of DT in teaching and learning CM throughout the stages of the FC mode*

FC Phases	Instructor Activities	Learner Activities	Supporting DT	Pedagogical Roles
Phase 1: Pre-class	Designing and digitizing IM (concept maps, instructional videos, lectures	Proactively access learning materials and study foundational theories. Complete basic quizzes.	LMS, YouTube, OneDrive, Canva, Mindmap, Gemini, Notebook LM	Support personalized learning and self-directed learning development.
Space: LMS Platform		Use AI tools to summarize learning content and formulate questions		
	Create discussion forums and online quizzes	Participate in online group discussions	LMS, MS Teams, Zoom	Foster interaction and collaborative learning.
Phase 2: In-class	Organize and facilitate classroom activities	Present problems, engage in group discussions, and participate in debates.	Padlet, LMS	Support idea visualization and stimulate critical thinking and intergroup interaction.
Space: Physical Classroom	Clarify misconceptions and consolidate key knowledge.	Solve real-world problem-based tasks and case studies		
Phase 3: Post-class	Evaluate learning outcomes.	Return to the LMS to complete reinforcement and extension activities	Quiz (LMS), Google Forms, LMS	Promote active learning and higher-order thinking skills
Space: LMS Platform	Collect feedback for instructional improvement	Revise mistakes and refine individual/ group learning products		Establish a continuous feedback loop between instructors and learners.

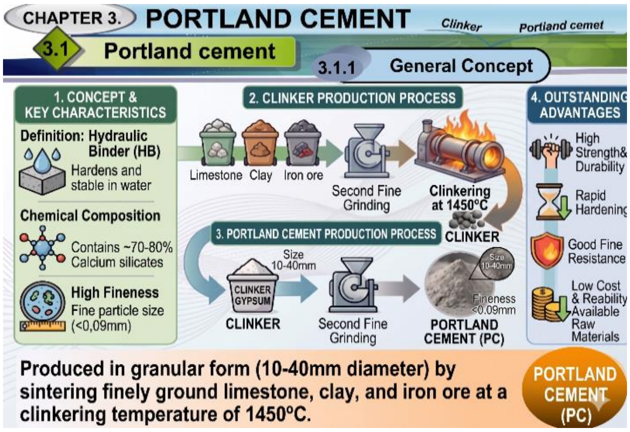

Figure 2. *Instructor utilizing NotebookLM and Gemini for instructional content design on the LMS*

Table 1. *Multimedia instructional resources within the LMS for the CM course*

No.	Category	Instructional Content	Format	Quantity
1	Core Textbooks	Chapter 1: Physical and Mechanical Properties of Materials Chapter 2: Natural Stone Chapter 3: Portland Cement Chapter 4: Construction Mortar	PDF	8
2	Concept Maps	Chapter 5: Cement Concrete Chapter 6: Asphalt and	JPG	8
3	Assessment Banks	Asphalt Concrete Chapter 7: Construction	Aiken	8
4	Instructional videos	Steel Chapter 8: Supplementary Materials	MP4	25

Through participation in these learning activities, students gradually became familiar with and utilized DT at a basic level for completing online quizzes, creating learning products, storing data, and organizing online group discussions (Figure 3). All IM generated by Gemini and NotebookLM were carefully reviewed and cross-checked by the instructor against officially published textbooks before being uploaded to the LMS, thereby ensuring academic accuracy and content reliability.

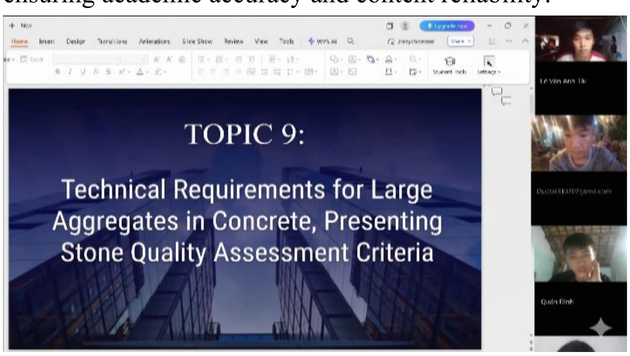

Figure 3. *Student utilization of Canva for report generation and MS Teams for collaborative group meetings*

3. Evaluation of curricular implementation for course section 125VLXD03

This cohort comprised 57 students. Preliminary classroom surveys indicated that nearly all participants possessed at least one internet-capable device (laptop or smartphone), providing a foundational advantage for the integration of digital technologies into the learning process.

3.1. Student Learning Attitudes

3.1.1. Learner Autonomy Indices

Student autonomy was quantified based on metrics including video lecture engagement duration, the frequency of pre-class resource access, and the completion rates of formative assessments. These activities were systematically tracked using the Job-Log functionality within the LMS. The extraction and analysis of this log data provided instructors with empirical evidence to evaluate authentic learning behaviors. This was achieved through the generation of correlation matrices representing various learning activities (Figure 4) and heat maps illustrating student interaction patterns with digital instructional resources (Figure 5).

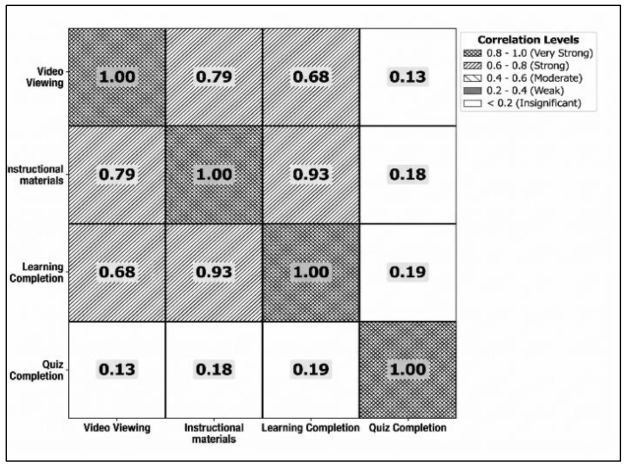

Figure 4. *Correlation matrix of student learning activities on the LMS*

The following observations were derived from the analysis of Figure 4:

- A very strong correlation coefficient of 0.93 between IM access and early learning completion indicates that highly engaged students proactively prepare for lessons well in advance. Although the system log data do not directly reflect cognitive quality, these behavioral patterns demonstrate robust time management and SRL abilities among learners.

- The correlation coefficient of 0.79 between video viewing and general resource access suggests that instructional videos serve as highly effective learning materials. Learners typically engage with video content prior to acquiring deeper knowledge through supplementary documents. This sequential learning path-characterized by 'video engagement first, documented depth later'-reflects an intentional and goal-oriented learning trajectory.

- Conversely, extremely low correlation values were observed regarding the speed of quiz completion (0.13, 0.18, and 0.19). This implies that extensive preparation - via video viewing or reading - did not significantly impact the time taken to finish assessments. Such results may stem from disproportionate difficulty levels in the quizzes or a lack of alignment between the provided resources and the assessment criteria.

Based on these findings, several pedagogical improvements are proposed:

- Incentivizing early engagement: instructors should initiate discussion forums early (e.g., during weekends) or offer minor academic incentives for accessing materials at least 24 hours prior to synchronous sessions to cultivate proactive study habits across the broader student cohort.

- Assessment alignment: a thorough review of the assessment content is necessary to ensure it accurately reflects the IM and appropriately challenges the learners.

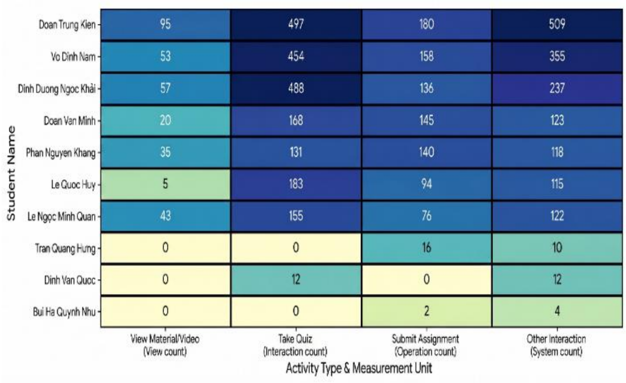

Figure 5. *Heat map depicting the differentiation of competency levels among student cohorts*

Caption:

View resources: measures the frequency with which students open IM (e.g., PDF documents, videos) or access external URLs - Measuring diligence

Quiz: encompasses the entire process from initiating an assessment and reviewing question summaries to the final official submission - Measuring effort

Assignment: aggregates all procedural operations, including file uploads, content updates, and verification of successful submission -Measuring digital literacy

Other interactions: includes supplementary activities such as reviewing gradebooks, accessing course announcements, or checking the academic schedule -Measuring self-discipline

The heat map in Figure 5 illustrates a clear divergence in academic performance and engagement among ten representative students. These ten students were selected using a stratified sampling method, representing three levels of interaction: high, medium, and low, corresponding respectively to the transition from dark blue hotspots to light yellow regions on the heatmap. The raw log dataset (logs_125VLXD03) was extracted from the Moodle LMS as unprocessed learning behavioral data. Therefore, the study aggregated the frequency of student interactions across four core behavioral variables (Figure 5). Subsequently, the data were normalized using the Min-Max scaling technique to transform all variables onto a common scale and minimize discrepancies among interaction types prior to heatmap visualization.

The results presented in Figure 5 indicate that the high-achieving cohort (e.g., Kien, Nam, Khai) is distinguished by dense, dark-shaded regions, indicating comprehensive and diligent interaction across all learning activities. Notably, engagement with IM shows the highest degree of variance, reflecting a significant disparity in theoretical study habits between the top-performing students and the rest of the class. Furthermore, the assessment columns received the highest interaction from both the high and average cohorts, suggesting that students prioritize activities with direct credit implications. Based on this visual data, immediate pedagogical intervention is required for the high-risk group (e.g., Hung, Quoc, Nhu), who exhibit minimal system interaction. Such competency-based segmentation enables instructors to implement tailored teaching strategies to suit diverse learner needs.

3.1.2. Academic Performance Outcomes

a. Formative assessments

Formative quizzes were integrated into every chapter to evaluate student self-study efficacy based on LMS resources (Figure 6).

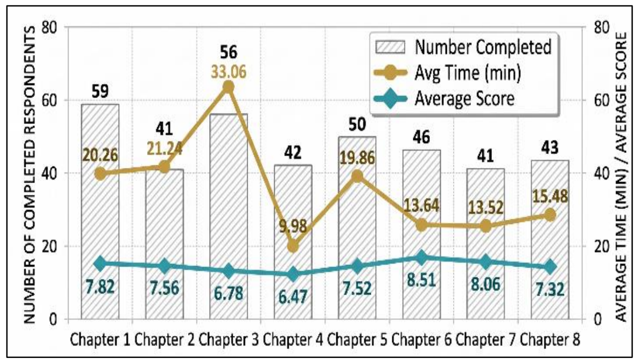

Figure 6. *Student academic performance trends across eight weekly assessments*

Analysis of the data in Figure 6 reveals several key findings:

- Participation attrition: a significant decline in participation was observed, dropping from 59 students (from week 2 onward, two students dropped the course, leaving the class with 57 students) in chapter 1 to an average of 41.43 in subsequent chapters - a 30% reduction. This finding may be attributed to the fact that Chapter 1 primarily reviews familiar high-school knowledge, whereas the subsequent chapters contain more specialized disciplinary content with greater academic workload, thereby increasing the risk of cognitive overload among first-year students.

- Engagement duration: chapter 3 recorded the peak engagement duration at 3.06 minutes per question (exceeding 30 minutes total), indicating either high content density or excessive complexity. Conversely, Chapter 4 exhibited the shortest completion times.

- Performance disparities: chapter 6 showed the highest efficiency, with a peak average score of 8.51 achieved within a relatively brief duration (13.64 minutes). In contrast, Chapter 4 presented the most significant concern, yielding the lowest average score (6.47) alongside the shortest completion time; this suggests that students may have engaged superficially without adequate conceptual preparation.

Based on these observations, the following refinements are proposed:

- Optimization of chapter 3: reduce cognitive load by segmenting content and simplifying overly complex questions to align with appropriate completion time

- Revision of chapter 4: review the question bank to address misalignment with instructional materials, while adding prerequisite checks and clearer feedback to improve learning quality.

- Retention strategies: address the 30% participation drop through automated reminders, micro-incentives, and data-driven interventions to sustain student engagement.

Table 3. *Synthesis of assessment components and weighting distribution according to the course syllabus*

Assessment category	Evaluation method	Component weight	Category weight
A1. Formative Assessment	A1.1 Attendance and Participation	50%	30%
	A1.2 Weekly Quizzes (8 Sessions)	50%	
	A1.3 Discussion Forums	Bonus Points	
A2. Mid-term Assessment	Group Thematic Project	100%	20%
A3. Summative Assessment	A3.1 Objective test	50%	50%
	A3.2 Individual Assignments	50%	

Final academic outcomes were derived from a weighted multi-component assessment framework (Table 3), visually represented in Figures 7 and 8. Each evaluation is governed by specific criteria designed not only to ensure subject matter mastery but also to foster digital literacy, soft skills, communication, and collaborative teamwork, …

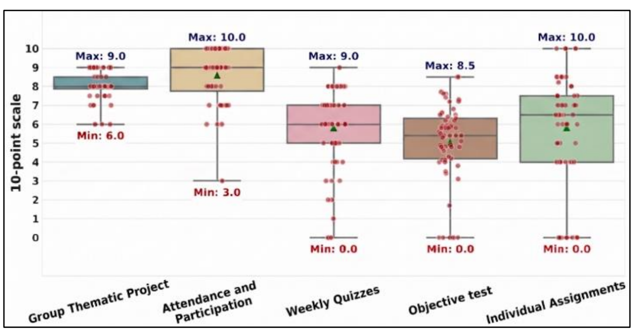

Figure 7. *Score Distribution analysis for course section 125VLXD03*

For multiple-choice examinations conducted on the LMS, the test items were extracted from a standardized question bank that had undergone quality validation. The assessment process incorporated randomization mechanisms to shuffle both the order of questions and answer options, combined with an automated grading system to minimize subjective bias. For essay-based assessments and group assignments, the grading process was required to strictly adhere to detailed assessment rubrics and current material standards. This approach helped maximize scoring consistency and maintain inter-rater reliability throughout the evaluation process.

Analysis of Figure 7 reveals several performance trends:

- Participation and attendance: this category yielded the highest scores, with a significant majority achieving between 9.0 and 10.0 (including 20 students with perfect scores).

- Mid-term evaluation: this component served as a stable performance indicator, with 100% of the cohort achieving a "Fair" grade or higher (minimum score of 6.0). This success is attributed to effective peer support and high levels of interaction during group-based thematic projects and collaborative problem-solving.

- Individual assignments: this area exhibited the greatest performance disparity. While several students (5 individuals) achieved scores of 10.0, a subset received significantly lower marks due to instances of academic dishonesty and plagiarism.

- Final objective examination: computer-based testing resulted in the lowest overall distribution, with scores clustering around the 5.0 mark and a notable absence of high-distinction results. This outcome suggests that first-year students still face challenges in synthesizing and retaining the broad spectrum of knowledge required for a comprehensive final exam.

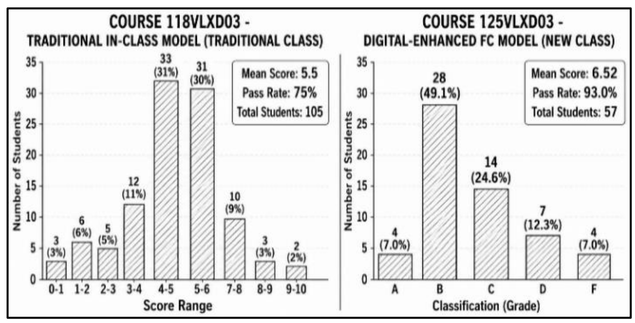

Figure 8. *Final grade distribution comparison [13]*

According to Figure 8, the cohort demonstrated a robust overall performance with an average score of 6.52. Students achieving a Grade B represented the overwhelming majority (nearly 50%), indicating that most learners successfully mastered the core curriculum knowledge. The course completion rate was exceptionally high at 93%, with only four students (7%) receiving a Grade F. This underscores the efficacy of both instructional delivery and student comprehension.

Notably, these outcomes reflect a significant improvement compared to the previous cohort (Class Code: 118VLXD03; Figure 8). Specifically, the class average score increased substantially from a relatively low baseline of 5.5 to 6.52. Concurrently, the passing rate experienced a remarkable leap from 75% to 93% (an 18% increase), demonstrating more equitable and effective learning outcomes upon transitioning from the traditional instruction model to the newly implemented framework.

Conversely, Figure 8 also reveals a distinct lack of high-tier academic breakthroughs, characterized by a minimal proportion of outstanding students (only four individuals achieving Grade A). While this represents a highly stable cohort with a commendable passing rate, additional pedagogical incentives and motivational strategies are required to stimulate upper-average students

(Grade B) to transition into the excellent performance tier (Grade A).

3.1.3. Student Feedback Survey

A post-course survey was conducted with 48 out of 57 students (an 84% response rate) to evaluate their preference between traditional lecturing and the FC model enhanced by DT. The results indicate (Figure 9, Table 4) that the modern approach outperformed traditional methods in 8 out of 11 criteria, specifically regarding temporal and spatial flexibility and the enriched learning experience provided by DT.

This suggests that for first-year students, who may still exhibit academic hesitancy or shyness, the instructor must re-evaluate coordination strategies to better facilitate interpersonal connections and engagement.

Table 4. *Evaluation Criteria and Survey Results of Learner Perceptions: Traditional Instruction vs. DT integrated FC*

No.	Evaluation Criteria	Traditional Teaching (students)	Digital-Enhance FC (students)
1	Ease of access	23	25
2	Visual and engaging presentation	23	25
3	Coverage of core knowledge in the syllabus	28	20
4	Coverage of extended knowledge in the syllabus	22	26
5	High level of interaction	39	9
6	Audience engagement	37	11
7	Cost effectiveness	22	26
8	Time flexibility	10	38
9	Multiple assessment components	20	28
10	Diverse learning experiences	12	36
11	Ability to use DT for learning support	16	32

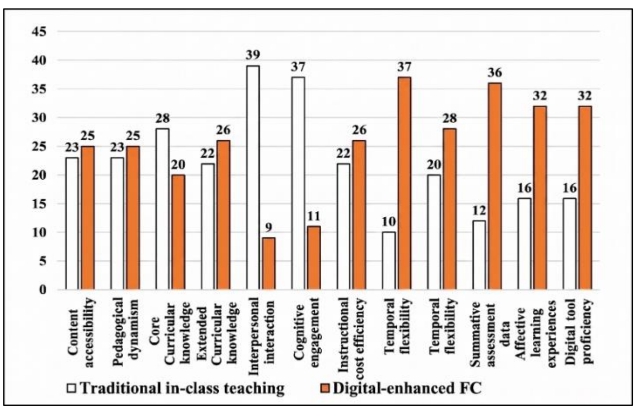

Figure 9. *Comparative Survey Results: Traditional in-class teaching vs Digital-Enhanced FC*

4. Discussion

The integration of digital technologies into the teaching of the CM course provides both opportunities and challenges for instructors in the context of Education 4.0, particularly in large-class settings. This section discusses the major findings of the study, compares them with relevant literature, and proposes directions for future research.

- Promotion of SRL: A very strong correlation coefficient (0.93) between access to learning materials and early learning activities indicates that the digital learning environment effectively promoted learner autonomy and SRL, consistent with the findings of J. W. You [14].

- Cognitive barriers: The very weak correlations (0.13 and 0.19) between quiz completion speed and prior preparation suggest that frequent interaction with digital learning materials did not immediately translate into improved assessment performance. Students still encountered cognitive barriers when transforming theoretical knowledge into problem-solving and test-taking skills. This finding implies that instructors should design learning tasks and assessments that are more aligned with students' cognitive readiness.

- Psychological inertia and resistance to change: Although the course pass rate reached 93%, the survey results revealed that only 9 out of 48 students (19%) preferred the new instructional model, compared with 39 out of 48 students favoring the traditional approach. This finding reflects the challenges of implementing innovative teaching methods for first-year students, who often experience psychological pressure during the transition from high school to university learning environments, consistent with the observations reported by Robin van der Velde [15].

- Learning analytics for early warning systems: The analysis of job-log data extracted from the LMS demonstrated that learning analytics can serve as an effective tool for monitoring student learning behaviors. Instead of waiting for midterm examination results, behavioral data enabled instructors to identify at-risk students early and provide timely intervention [16]. In this study, the 30% decline in quiz participation beginning in Chapter 2 represented a significant warning signal, indicating that learner engagement in digital environments may decrease rapidly without appropriate retention and interaction strategies.

5. Conclusion

The integration of DT with the FC and LMS in the CM course has demonstrated immediate efficacy in fostering student autonomy and self-regulated learning abilities. Furthermore, this framework establishes a scalable paradigm adaptable to other engineering disciplines. The core findings and recommended enhancements are summarized as follows:

- Enhanced Learning Efficacy: the model significantly bolstered student proactivity, resulting in a 93% course completion rate with an overall average score of 6.52.

- Data-Driven Early Warning System: learning analytics derived from system log data (job-logs) and heatmaps enabled the early identification of disengaged students by the third week of the semester, allowing timely pedagogical interventions by the instructor.

- The application of DT through AI and LMS, if lacking the high-touch elements of direct interaction and deep psychological connection between instructors and learners, will create learning barriers, particularly for first-year students.

To further optimize the model, the study proposes several recommendations:

- Establishing Digital Academic Discipline: implementing a mandatory cooldown/waiting interval between quiz attempts is recommended to mitigate random-guessing behaviors and compel students to review the instructional materials.

- Optimizing Learning Resources and Assessment: instructional videos should be designed to be concise (under 10 minutes) and highly focused on practical engineering applications. Concurrently, formative quiz components should be segmented and strictly aligned with each video segment to minimize student cognitive overload.

- Strengthening Synchronous Interaction: in-class interactive activities between instructors and students, as well as collaborative peer discussions, should be enhanced to increase classroom engagement.

Future research will focus on expanding the evaluation scope to other engineering courses and control groups to validate and refine this pedagogical model.

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