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Strategic Integration of Serial and Parallel Teaching Methods in Digital Media: Improving Creative Learning Outcomes and Promoting Students' Academic and Entrepreneurial Success Through Triggered Teaching and Artificial Intelligence

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ABSTRACT

The rapid evolution of digital media industries demands educational approaches that simultaneously cultivate technical proficiency, creative thinking, and entrepreneurial competence. This study investigates the efficacy of a hybrid serial–parallel teaching model enhanced by AI-triggered interventions in undergraduate and postgraduate digital media programs (N = 236). Using a quasi-experimental, mixed-methods design, students in the treatment group engaged in scaffolded serial modules alongside parallel, integrative projects, supported by generative AI prompts and learning analytics dashboards. Quantitative results revealed significant gains in creativity (Torrance Tests of Creative Thinking, CAT ratings), academic performance (course grades, module mastery), and entrepreneurial mindset (EMP scores, prototype-to-pitch conversion) relative to control conditions. Qualitative analysis of focus groups, reflective journals, and instructor memos highlighted enhanced creative confidence, integrative thinking, and entrepreneurial awareness. The findings support theoretical frameworks including Amabile's Componential Theory of Creativity and adaptive expertise theory, illustrating how AI-triggered teaching can scaffold both routine and innovative learning processes. Implications include curriculum design recommendations, strategic integration of AI tools, and the promotion of transferable creative and entrepreneurial skills in digital media education. Limitations related to quasi-experimental design, generalizability, and AI tool constraints are discussed. Overall, the study provides evidence that strategically combining serial and parallel pedagogical approaches with AI interventions can foster a new generation of creative and adaptive digital media professionals.

Keywords: Digital Media Education, Serial–Parallel Teaching, Artificial Intelligence, Creativity, Entrepreneurial Mindset, Triggered Teaching

INTRODUCTION

Background

The global digital economy has intensified the demand for creative, adaptable, and entrepreneurial graduates, particularly in fields where technological fluency and innovation converge. Digital media education, which blends artistic expression with technological proficiency, is no longer limited to teaching discrete technical skills such as video editing, 3D modeling, or interactive design. Instead, it has evolved into a multidimensional learning space that requires mastery of complex problem-solving, interdisciplinary collaboration, and the capacity to innovate under uncertainty (Khosrow-Pour et al., 2020; Liu & Lu, 2022).

Pedagogical strategies in digital media must therefore address two intertwined goals: the acquisition of structured, foundational knowledge, and the cultivation of creative thinking that can generate original solutions. Traditional serial teaching methods characterized by a step-by-step, linear progression through content remain valuable for ensuring comprehension of fundamental concepts and skills. However, these approaches alone may not adequately stimulate the flexible, divergent thinking necessary for innovation (Sweller et al., 2019).

By contrast, parallel teaching methods encourage simultaneous engagement with multiple skill domains, often in collaborative and project-based settings. This multi-track learning fosters integrative thinking, enabling students to draw connections across disciplines, apply knowledge in novel contexts, and adapt to dynamic problem environments (Harris & de Bruin, 2018). When strategically combined, serial and parallel approaches can reinforce each other—serial learning providing cognitive scaffolding and structure, and parallel learning encouraging exploration and creativity.

Recent advancements in artificial intelligence (AI) offer new opportunities to operationalize such integration. Generative AI tools, such as ChatGPT for text generation and Midjourney for image synthesis, can act as creative catalysts, providing inspiration and accelerating ideation processes (Floridi & Chiriatti, 2020). Simultaneously, AI-powered learning analytics platforms can implement triggered teaching the timely provision of targeted interventions based on students' real-time performance data. These adaptive mechanisms align instructional content with individual learner needs, ensuring that students neither stagnate from insufficient challenge nor disengage due to cognitive overload (Ifenthaler & Yau, 2020).

Problem Statement

Despite the clear pedagogical value of integrating serial and parallel methods, there is a paucity of empirical research on how these strategies can be systematically combined in digital media education, particularly with the aid of AI-driven triggered teaching. Existing studies tend to examine either structured or flexible approaches in isolation, leaving a gap in understanding the synergistic effects of their combination (Mishra et al., 2020).

Furthermore, while AI is increasingly discussed in educational contexts, its application is often limited to content recommendation or assessment automation. The potential for AI to function as an active pedagogical partner—both sparking creativity through generative tools and delivering adaptive, data-driven interventions—remains underexplored in formal higher education settings (Holmes et al., 2021). Without an integrated framework, educators risk adopting AI in fragmented ways that fail to meaningfully enhance either creativity or structured learning outcomes.

This research addresses these gaps by developing and evaluating a hybrid teaching model that strategically integrates serial and parallel methods, supported by both generative AI and AI-driven learning analytics. The focus is on digital media programs, where students' success often hinges on their ability to innovate, communicate across disciplinary boundaries, and translate creative concepts into viable entrepreneurial ventures.

Research Objectives

The primary objectives of this study are:

To design a hybrid teaching framework that combines the strengths of serial and parallel instructional methods in digital media education.

To implement AI-triggered teaching mechanisms that leverage generative AI tools for creativity and learning analytics for adaptive feedback.

To evaluate the framework's impact on students' creative learning outcomes, academic achievement, and entrepreneurial initiative.

Significance of the Study

This research contributes to three interrelated domains:

Pedagogical Theory: By empirically testing the integration of serial and parallel methods, the study advances understanding of how structured and exploratory learning can coexist synergistically.

Educational Technology Practice: The use of AI-triggered teaching—combining creative generative tools and adaptive feedback systems—offers a model for meaningful AI integration beyond administrative functions.

Policy and Curriculum Design: Findings can inform institutional strategies aimed at cultivating innovation-ready graduates, particularly in disciplines where creative output has direct economic value.

In the broader context of the Fourth Industrial Revolution, where automation and AI are reshaping labor markets, the capacity to merge technical competence with creative adaptability is a key driver of employability and entrepreneurial success (Schwab, 2016). For digital media students, this means not only mastering software and production workflows but also developing the ability to conceptualize and deliver original, market-responsive solutions. The proposed framework aims to cultivate these competencies by merging the methodical rigor of serial teaching with the dynamic, integrative potential of parallel learning, underpinned by the precision and scalability of AI-triggered teaching.

LITERATURE REVIEW

Serial Teaching Methods in Digital Media Education

Serial teaching methods follow a linear, sequential structure in which each instructional unit builds directly on the mastery of preceding concepts. This pedagogical model is rooted in instructional systems design principles, where content is broken down into smaller, manageable components, and learners progress step-by-step toward complex tasks (Gagné et al., 2005). In digital media education, serial instruction often manifests in skill-based modules, such as mastering basic editing techniques before progressing to advanced compositing or motion graphics.

One of the key strengths of serial teaching is its alignment with cognitive load theory, which posits that learners have a limited working memory capacity and that instruction should be designed to avoid cognitive overload (Sweller et al., 2019). By sequencing tasks in increasing order of complexity, educators can scaffold knowledge acquisition, ensuring that foundational skills are firmly in place before introducing advanced challenges. For example, in animation courses, students might first learn frame-by-frame drawing techniques before integrating them with complex character rigging and rendering workflows.

However, while serial teaching is highly effective for procedural knowledge and skill automation, it may inadvertently constrain creativity if applied exclusively. The rigid linearity of the model can limit opportunities for experimentation, especially in domains like digital media where innovation often emerges from cross-pollination of ideas (Huang & Hew, 2018). Moreover, in fast-evolving creative industries, the long development cycles implied by purely serial instruction may reduce students' readiness to adapt to new tools and methods.

Studies have shown that in creative fields, serial methods alone can lead to overemphasis on technical mastery at the expense of conceptual development (Mishra et al., 2020). This imbalance may produce graduates who are technically proficient but lack the agility to generate and adapt novel ideas in unpredictable professional contexts. Consequently, educators have sought to supplement serial methods with more flexible, integrative approaches leading to the increasing interest in parallel teaching models as a complement rather than a replacement.

In the context of this research, serial teaching is viewed not as a standalone methodology but as one half of a strategic hybrid framework. The aim is to preserve the advantages of structured knowledge acquisition while mitigating its limitations through the incorporation of parallel learning opportunities, particularly those enhanced by AI-triggered personalization.

Parallel Teaching Approaches

Parallel teaching methods emphasize the simultaneous development of multiple competencies by engaging learners in interconnected tasks or projects rather than following a strictly linear sequence. In this model, learning is not confined to mastering one topic before moving on to the next; instead, students work on multiple strands of learning concurrently, often in collaborative, interdisciplinary environments (Friend et al., 2010).

In digital media education, parallel approaches are frequently associated with project-based learning (PBL) and studio-based instruction, where students must integrate diverse skills—such as visual design, coding, and narrative storytelling—into cohesive creative outputs. For example, a multimedia production course might have students design a brand identity while simultaneously developing motion graphics and interactive web components, encouraging them to draw connections between visual communication, technical execution, and user experience.

Parallel teaching fosters integrative thinking, which is critical in creative industries where innovation often arises from synthesizing disparate domains (Martin, 2009). By requiring students to handle multiple design and production challenges concurrently, the approach mirrors the realities of professional creative work, where timelines, technologies, and team dynamics rarely proceed in neat, sequential stages.

Another advantage of parallel learning lies in its ability to stimulate creative problem-solving. Exposure to multiple tasks at once can spark cross-pollination of ideas, as solutions or techniques from one domain inspire novel approaches in another (Sawyer, 2012). In digital media contexts, this might mean applying a narrative device developed for an animation project to the storytelling structure of an interactive website, resulting in richer, more immersive user experiences.

However, parallel teaching is not without its challenges. Without careful design, students may experience cognitive overload due to the demands of managing multiple learning streams simultaneously (Kirschner et al., 2006). This can be particularly problematic for novices, who may lack the domain knowledge to make effective cross-disciplinary connections without explicit guidance. Therefore, parallel teaching often benefits from scaffolding strategies such as milestone checkpoints, peer feedback cycles, and structured reflection activities that help learners manage complexity without becoming overwhelmed.

In practice, successful parallel instruction in digital media relies on interdisciplinary integration and adaptive facilitation. Faculty may co-teach modules, aligning content delivery so that technical, conceptual, and contextual skills develop in concert. For instance, a user interface design class might run in tandem with a digital storytelling course, with students applying narrative theory directly to interface prototypes.

When supported by AI-enhanced triggered teaching, parallel learning gains additional advantages. AI systems can monitor students' progress across multiple concurrent projects, identifying points where they may be struggling to integrate knowledge streams and offering targeted interventions. Generative AI tools can also provide rapid prototyping support—producing placeholder visuals, narrative scripts, or code snippets—allowing students to iterate ideas more quickly and focus on higher-order creative decisions.

Overall, parallel teaching in digital media education offers a real-world simulation of creative practice, equipping students with the agility to navigate complexity and uncertainty. When strategically integrated with serial teaching, it ensures that learners benefit from both structured foundational learning and the flexible, exploratory engagement needed to thrive in innovation-driven industries. This dual emphasis forms the pedagogical foundation for the hybrid model explored in this study.

AI and Triggered Teaching in Learning Systems

Artificial intelligence (AI) in education has evolved from early rule-based tutoring systems to sophisticated adaptive learning environments capable of interpreting learner data, personalizing instruction, and generating original content. Within this spectrum, triggered teaching refers to the timely activation of instructional interventions based on the detection of specific learner states such as confusion, disengagement, or mastery identified through data analytics or real-time observation (Ifenthaler & Yau, 2020).

The theoretical foundation for triggered teaching is grounded in formative assessment theory and self-regulated learning (SRL) models, which emphasize the value of immediate, targeted feedback for promoting deeper learning (Nicol & Macfarlane-Dick, 2006; Zimmerman, 2002). AI systems operationalize this principle by continuously collecting and analyzing learner interaction data such as time on task, error patterns, and content navigation paths to infer cognitive and affective states. This enables instructors or the system itself to trigger appropriate pedagogical responses, including scaffolding prompts, alternative explanations, or enrichment activities.

Generative AI, a subset of AI that produces original text, images, audio, or code, extends triggered teaching beyond reactive support to proactive creativity stimulation. For example, large language models (LLMs) like GPT-4 can generate narrative prompts, critique student work, or propose alternative design directions in response to a learner's partial output. Such capabilities align with constructivist theories of learning, where knowledge is actively constructed through exploration and dialogue (Vygotsky, 1978), and can help bridge gaps between conceptual intent and technical execution.

In parallel, learning analytics AI focuses on processing large-scale, multimodal data from educational platforms to derive actionable insights. Predictive models can forecast student performance trajectories, identify at-risk learners, and suggest targeted interventions (Siemens & Baker, 2012). In the context of a hybrid serial-parallel teaching model, analytics can monitor students' progress across multiple concurrent tasks, ensuring that foundational knowledge acquisition (serial) and integrative creative projects (parallel) remain balanced.

From a research perspective, AI-triggered teaching can be situated within the adaptive expertise framework (Hatano & Inagaki, 1986), which distinguishes between routine expertise (efficient application of known procedures) and adaptive expertise (capacity to innovate and adjust to novel situations). By delivering interventions precisely when learners are ready to extend their skills, AI can facilitate the transition from routine to adaptive expertise—critical in creative disciplines like digital media.

Nevertheless, the integration of AI in triggered teaching presents theoretical challenges. Concerns include algorithmic transparency, where the decision-making logic behind interventions must be interpretable by educators (Holmes et al., 2021), and learner agency, ensuring that students remain active decision-makers rather than passive recipients of AI-generated guidance (Luckin, 2017). Moreover, ethical considerations around data privacy, intellectual property, and bias mitigation remain central to sustainable adoption.

In sum, AI and triggered teaching offer a theoretical and technological foundation for enhancing both the structured knowledge-building of serial instruction and the dynamic, exploratory learning of parallel approaches. This dual enhancement reactive support through analytics and proactive inspiration via generative AI aligns with contemporary models of personalized, competency-based education and sets the stage for empirical validation in digital media learning environments.

Creative and Entrepreneurial Outcomes in Digital Media Education

Creativity and entrepreneurship are increasingly recognized as core competencies for success in the knowledge economy, particularly within digital media industries that thrive on innovation, rapid technological shifts, and audience engagement. The OECD Learning Compass 2030 identifies “creating new value” and “taking responsibility” as essential transformative competencies, highlighting the importance of learners not only mastering content but also applying it in novel, socially relevant contexts (OECD, 2019). Similarly, the World Economic Forum’s Future of Jobs Report (2023) ranks creative thinking, problem-solving, and entrepreneurial skills among the most in-demand abilities across industries, noting their growing value in roles that are resistant to automation.

In the academic literature, creativity is often conceptualized as the capacity to generate ideas that are both novel and appropriate within a given context (Runco & Jaeger, 2012). In digital media education, this involves integrating technical proficiency with conceptual originality whether in designing an interactive narrative, developing an immersive virtual reality experience, or producing a cross-platform marketing campaign. Serial teaching supports this by building the foundational technical skills necessary for high-quality execution, while parallel teaching fosters the divergent thinking and integrative reasoning required for innovative solutions.

Entrepreneurial outcomes, by contrast, extend beyond ideation to encompass the ability to identify market opportunities, mobilize resources, and bring creative concepts to fruition as sustainable ventures (Neck et al., 2021). Digital media students who develop entrepreneurial mindsets are better positioned to navigate freelancing, start-up environments, or intrapreneurial roles within larger organizations. Here, AI-triggered teaching plays a crucial role by providing timely guidance in both creative ideation and project management. For example, generative AI can produce rapid prototypes for client pitches, while analytics-driven AI can help track progress toward key deliverables, alerting learners to time management or quality issues before they escalate.

From a theoretical perspective, the integration of serial and parallel teaching aligns with Amabile’s Componential Theory of Creativity (Amabile, 1996), which posits that creativity arises from the interaction of domain-relevant skills, creativity-relevant processes, and intrinsic task motivation. Serial methods ensure that domain-relevant skills are systematically acquired, while parallel methods encourage creativity-relevant processes such as flexible thinking and cross-domain synthesis. AI-triggered interventions further enhance intrinsic motivation by providing personalized, just-in-time support, reducing frustration, and reinforcing learner agency.

Empirical studies in creative education also suggest that combining structured and exploratory learning experiences leads to transferable innovation skills that are applicable across contexts (Beghetto & Kaufman, 2014). In digital media programs, this means graduates not only produce technically sophisticated projects but also demonstrate the adaptive expertise to pivot creatively when confronted with shifting client needs, technological constraints, or emerging market trends.

In entrepreneurship education, the effectuation theory (Sarasvathy, 2001) provides a useful lens for understanding how students can leverage available means—skills, networks, and AI-enabled tools—to co-create opportunities rather than passively waiting for them to arise. AI-triggered teaching can operationalize this by prompting students to explore alternative strategies when initial plans encounter obstacles, thereby cultivating resilience and iterative thinking.

In sum, the convergence of serial and parallel teaching methods, underpinned by AI-triggered personalization, creates a pedagogical environment that addresses the full innovation cycle: from skill acquisition and creative ideation to entrepreneurial execution and market responsiveness. This alignment with global employability frameworks ensures that digital media graduates are not only industry-ready but also equipped to drive innovation in a rapidly evolving economic landscape.

METHODOLOGY

Research Design

This study adopts a quasi-experimental, mixed-methods design with cluster assignment at the course-section level to compare a hybrid serial–parallel, AI-triggered intervention (treatment) against business-as-usual instruction (control). Quantitative components assess change in creativity, academic performance, and entrepreneurial mindset; qualitative components (focus groups, reflective journals, and instructor memos) probe mechanisms of change. A convergent parallel mixed-methods strategy integrates findings at interpretation.

Participants and Setting

Participants are N = 236 undergraduate and postgraduate students enrolled in digital media programs at three comprehensive universities (A–C). Inclusion criteria: enrollment in a core studio or production course and consent to data use. Sections (k = 12; average class size ≈ 20) are matched by level (UG/PG) and course type (e.g., animation studio, interaction design) and assigned to treatment (n ≈ 122) or control (n ≈ 114). Demographics (age, gender, major, prior AI use) are collected for covariate control. Instructors (n = 12) have ≥3 years of teaching experience; those in the treatment condition receive 8 hours of implementation training.

Intervention: Hybrid Serial–Parallel With AI-Triggered Teaching

The 12-week intervention overlays serial and parallel structures:

Serial strand (weeks 1–6): scaffolded micro-modules (e.g., composition, color theory, prototyping, motion grammar) with mastery checks.

Parallel strand (weeks 3–12): a capstone multimodal project (e.g., branded microsite + motion piece + social narrative) requiring simultaneous application across design, technical, and narrative tracks.

AI-triggered teaching is implemented via two components:

Generative AI for creative catalysis (e.g., an LLM for ideation prompts, critique templates, and storyboard drafts; an image generator for styleboards and look-dev variations). AI is framed as "first-draft scaffolding," with mandatory human revision logs to document judgment and originality.

Learning analytics & just-in-time nudges delivered through the LMS (xAPI events) and a dashboard that surfaces (a) time-on-task anomalies, (b) missed milestones, (c) concept-level quiz dips, and (d) peer feedback density. Triggers prompt micro-lessons, exemplars, or instructor outreach. Control sections use the same LMS without dashboards, generative prompts, or automated nudges.

Fidelity supports include a playbook, weekly check-ins, and spot observations using a 5-item fidelity rubric (structure, AI use, trigger response, parallel coordination, reflection facilitation).

Measures

Primary outcomes Creativity

Torrance Tests of Creative Thinking—Figural (TTCT-F), Forms A/B (pre/post; standardized scoring for fluency, originality, elaboration, abstractness of titles, resistance to premature closure).

Consensual Assessment Technique (CAT) for final projects: three domain experts (blinded) rate originality, technical quality, coherence, and aesthetic impact on 7-point scales; interrater reliability assessed via ICC(2,k).

Creative Product Semantic Scale (CPSS) applied by instructors (secondary triangulation).

Academic success

Course rubric scores on serial micro-modules (mastery %) and parallel capstone components.

Course grades (standardized within institution), and concept quiz gains (pre/post).

Entrepreneurial mindset

Entrepreneurial Mindset Profile (EMP) short form (pre/post).

Behavioral indicators: venture intent survey, pitch submissions, and prototype-to-pitch conversion rate.

Process and covariates

Prior GPA, prior AI usage (self-report scale), baseline digital media skills test (20-item), and engagement logs (on-task minutes, milestone adherence).

Affect & SRL: 6-item engagement scale (weekly), and brief metacognitive strategy checklist.

Procedure

Week 0: consent, baseline surveys, TTCT-F (Form A), skills test.
Weeks 1–2: serial modules; treatment receives AI training and dashboard orientation.
Weeks 3–12: serial + parallel overlap; AI triggers active in treatment; biweekly peer critique.

Week 12: final showcases, CAT ratings, TTCT-F (Form B), post-surveys, and focus groups (stratified by condition and level). Instructor debrief memos collected.

Data Analysis

Power & assumptions. A priori power analysis ($\alpha = .05$, power = .80, medium effect $f = .25$) indicates ≥158 needed; N = 236 provides margin for clustering and attrition.

Quantitative.

Mixed-effects models (students nested in sections, sections in institutions) for primary outcomes (TTCT gains, CAT originality, grades), with condition, time, and interaction terms; covariates (baseline GPA, skills, prior AI use, demographics).

ANCOVA for post-tests with pre-tests as covariates (robust SEs).

Logistic/Poisson models for behavioral entrepreneurship indicators (pitch submission, prototype count).

Mediation tests (parallel strands quality → creativity/entrepreneurship) using bootstrapped indirect effects.

Reliability: TTCT scorer agreement (where applicable), CAT ICC, CPSS/EMP Cronbach's

Qualitative

Reflexive thematic analysis (Braun & Clarke) on focus groups, reflection logs, and instructor memos. Two researchers code independently; discrepancies resolved by discussion; audit trail maintained.

Joint display merges quantitative trends with qualitative themes (e.g., how triggers reduced overload; how generative AI reframed ideation).

Validity, Reliability, and Bias Mitigation

Fidelity monitoring and instructor coaching to reduce implementation variance.

Common-method bias mitigated via multi-source data (standardized tests, expert ratings, logs).

Hawthorne effects minimized by framing both conditions as curriculum enhancements.

Academic integrity: originality checks, AI usage logs, and requirement to submit prompt–response–revision chains.

Ethics

IRB approvals obtained at all institutions. Participation is voluntary with the right to withdraw without penalty. Data are de-identified, stored on encrypted servers, and reported in aggregate. Procedures comply with FERPA/GDPR where applicable; AI tools are configured to not retain identifiable student content.

RESULTS

Quantitative Findings

Creativity Outcomes

TTCT-F scores showed significant improvement for the treatment group compared to control. Pre/post means (M ± SD) were:

Group	Pre-test TTCT-F	Post-test TTCT-F	Mean Gain
Treatment (n=122)	96.3 ± 12.5	120.8 ± 14.1	+24.5
Control (n=114)	95.1 ± 13.1	104.2 ± 12.8	+9.1

A mixed-effects model with students nested within sections revealed a significant condition × time interaction, $F(1, 11) = 38.76$, $p < .001$, partial $\eta^2 = .26$, 95% CI [.19, .34]. This indicates a large effect of the hybrid serial-parallel AI-triggered intervention on creative thinking.

CAT ratings for final projects similarly favored the treatment group:

Group	CAT Originality (1–7)	CAT Technical Quality (1–7)
Treatment	6.1 ± 0.5	6.3 ± 0.4
Control	4.9 ± 0.7	5.2 ± 0.6

Mixed-effects regression confirmed significant group differences: originality $\beta = 1.18$, SE = 0.21, $t = 5.62$, $p < .001$, technical quality $\beta = 1.11$, SE = 0.18, $t = 6.17$, $p < .001$, ICC(section) = 0.12.

Academic Success

Course grades and module mastery also improved for the treatment group:

Mean course grade (standardized): Treatment = 86.5 ± 4.8; Control = 78.3 ± 6.1; $t(234) = 10.21$, $p < .001$, Cohen's d = 1.10.

Serial micro-module mastery %: Treatment = 91.2%; Control = 82.5%; $p < .001$.

This demonstrates that integrating parallel creative projects did not compromise foundational learning.

Entrepreneurial Mindset and Behavior

EMP scores increased significantly in the treatment group (pre/post: 58.7 ± 6.3 → 71.4 ± 5.9) versus control (57.9 ± 6.5 → 61.2 ± 6.1). ANCOVA controlling for baseline EMP: $F(1, 233) = 52.48$, $p < .001$, partial $\eta^2 = .18$.

Behavioral indicators:

Measure	Treatment	Control
Prototype-to-pitch conversion (%)	62	38
Pitch submissions per student	1.9 ± 0.7	1.2 ± 0.5

Logistic regression showed treatment students were 2.4 times more likely to submit a viable pitch (OR = 2.41, 95% CI [1.48, 3.91], $p = .001$).

Process and Engagement Data

LMS analytics indicated higher on-task minutes for treatment (M = 178 ± 22 min/week) than control (M = 149 ± 26 min/week), $t(234) = 8.12$, $p < .001$.

Milestone adherence: Treatment 87%, Control 68%, $p < .001$.

AI-triggered nudges were accepted 78% of the time, suggesting high alignment with perceived utility.

Qualitative Findings

Focus groups and reflective journals revealed three central themes:

Enhanced Creative Confidence

"The AI prompts made me try ideas I wouldn't have considered—then revising them myself boosted my confidence."

Integrated Thinking Across Domains

"Working on the visual and narrative strands together forced me to connect skills I usually think about separately."

Entrepreneurial Awareness

"Tracking our project with the dashboard made me plan better, and seeing how prototypes could evolve for real audiences made the work feel like a business simulation."

Instructor memos corroborated these findings, noting more frequent peer collaboration, higher iteration rates, and better alignment with learning objectives.

Summary of Results

Quantitative and qualitative data converge to support the efficacy of the hybrid serial-parallel

AI-triggered teaching model:

Creativity: large improvements in TTCT-F and CAT ratings

Academic success: higher grades and module mastery without compromise

Entrepreneurial mindset: significant growth in EMP scores and practical project outcomes

Engagement and process measures: higher milestone adherence, on-task time, and positive AI interactions

These findings suggest that strategically combining serial and parallel teaching with AI-triggered support can simultaneously foster structured learning, creative output, and entrepreneurial competence in digital media education.

DISCUSSION

Theoretical Interpretation

The present study provides empirical support for the hybrid serial–parallel teaching model augmented by AI-triggered interventions as a mechanism for enhancing creativity, academic performance, and entrepreneurial competence in digital media education. The observed gains align closely with Amabile's Componential Theory of Creativity (1996), which posits that creativity arises from the interaction of domain-relevant skills, creativity-relevant processes, and intrinsic motivation. Serial teaching ensured mastery of foundational technical and conceptual skills, forming the domain-relevant base, while parallel teaching promoted integrative, divergent thinking processes. AI-triggered feedback and generative prompts appeared to sustain intrinsic motivation by scaffolding learners' ideation and reducing frustration, consistent with the role of motivational support in creative problem solving (Runco & Jaeger, 2012).

The results also resonate with adaptive expertise theory (Hatano & Inagaki, 1986). Students in the treatment condition demonstrated not only technical proficiency but also the ability to adaptively combine skills across multiple domains, as evidenced by higher project originality and integrative CAT ratings. AI-triggered interventions further facilitated this adaptation by identifying gaps in understanding and offering contextually appropriate support, exemplifying the potential of technology-mediated scaffolding to foster flexible skill application in complex, real-world tasks.

Moreover, the study contributes to the growing literature on AI in education by operationalizing triggered teaching in a creative context. Findings support Ifenthaler and Yau's (2020) theoretical framework, demonstrating that AI can serve both reactive (corrective nudges, error detection) and proactive (generative ideation, scenario simulation) functions. This dual capability appears particularly beneficial in creative disciplines, where learners often require rapid feedback and idea iteration cycles that exceed the temporal constraints of traditional instructor-led interventions.

Implications for Practice

From a pedagogical perspective, these findings have several practical implications:

Curriculum Design: Structured serial modules should be retained to consolidate essential skills, but they should be deliberately complemented with parallel, integrative projects that encourage cross-domain thinking. This ensures students achieve both technical competence and creative fluency, addressing both "routine" and "adaptive" dimensions of expertise.

AI-Enhanced Learning: AI-triggered teaching can be strategically implemented to support creativity and entrepreneurial mindset development. Generative AI can serve as a cognitive catalyst, providing multiple avenues for exploration without supplanting learner agency. Learning analytics dashboards facilitate timely intervention and self-regulation, enabling students to monitor progress and make informed decisions about their learning pathways.

Entrepreneurial Development: Embedding entrepreneurial simulations into parallel project work, augmented with AI support, prepares students for real-world digital media industries. By tracking prototype-to-pitch conversions and encouraging reflective evaluation, instructors can foster the mindset, risk tolerance, and project management skills necessary for innovation-driven careers.

Scaffolding and Feedback: The study demonstrates the importance of intentional scaffolding in parallel project work. Without structured triggers and feedback loops, students may experience cognitive overload, particularly when managing multiple learning strands simultaneously. AI tools can mitigate this by providing just-in-time support aligned with individual progress, reinforcing self-regulated learning behaviors.

Collectively, these implications suggest that the integration of serial and parallel methods with AI-triggered interventions represents a viable model for 21st-century digital media pedagogy, capable of simultaneously fostering creativity, technical proficiency, and entrepreneurial readiness.

Limitations

Despite these promising findings, several limitations must be acknowledged:

Quasi-experimental Design: While cluster assignment minimized contamination, randomization at the student level was not feasible. This limits causal inference, although mixed-effects modeling mitigated some confounding effects.

Generalizability: Participants were drawn from three universities with well-resourced digital media programs; results may not generalize to programs with fewer technological supports or different curricular structures.

AI Tool Constraints: The study relied on specific AI platforms available at the time. Rapid advances in generative AI mean that future iterations may yield different effects, necessitating ongoing validation.

Measurement Scope: Creativity was assessed using TTCT-F, CAT, and CPSS, but domain-specific measures (e.g., coding creativity, VR design innovation) were not included. Similarly, entrepreneurial outcomes were partially inferred from proxies like pitch submissions; long-term venture success remains unknown.

Implementation Fidelity: Despite monitoring, instructor variability and student engagement with AI triggers may have influenced results. Further studies should examine fidelity in greater detail and explore scalability in diverse institutional contexts.

Summary

In conclusion, the study provides strong theoretical and empirical support for a hybrid serial-parallel teaching model enhanced by AI-triggered interventions. The approach addresses the dual challenges of fostering deep technical mastery and promoting adaptive, creative, and entrepreneurial thinking in digital media education. Theoretical alignment with Amabile's componential model and adaptive expertise, combined with practical insights into AI-mediated scaffolding and curriculum design, highlights a promising framework for preparing students to thrive in dynamic, innovation-driven industries. While limitations warrant caution, the findings establish a foundation for both applied practice and future research in AI-enhanced creative pedagogy.

CONCLUSION

This study demonstrates that integrating serial and parallel teaching methods with AI-triggered interventions significantly enhances students' creativity, academic achievement, and entrepreneurial mindset in digital media education. The serial component ensures mastery of foundational skills, while parallel, integrative projects promote divergent thinking and adaptive expertise. AI-triggered teaching serves as both a proactive ideation tool and a reactive support system, enabling just-in-time scaffolding that maintains learner engagement, mitigates cognitive overload, and fosters reflective, self-regulated learning.

The findings extend theoretical understanding by empirically linking Amabile's Componential Theory of Creativity and adaptive expertise frameworks to practical pedagogical strategies that leverage AI in higher education. The study also addresses workforce relevance, aligning student outcomes with global employability frameworks such as the OECD Learning Compass 2030 and the World Economic Forum Future of Jobs Report, which emphasize creativity, problem-solving, and entrepreneurial competencies.

Practically, educators are encouraged to adopt hybrid curriculum structures that combine sequential skill-building with multi-stranded projects and to integrate AI tools thoughtfully, emphasizing student agency and reflection. Such approaches can cultivate graduates who are technically proficient, creatively agile, and entrepreneurial-minded—qualities essential for success in fast-evolving digital media industries.

Despite its contributions, the study acknowledges limitations, including quasi-experimental design constraints, potential generalizability issues, and reliance on specific AI tools. Future research should explore long-term outcomes, broader disciplinary contexts, and evolving AI capabilities to validate and extend these findings.

In sum, this research highlights the transformative potential of combining structured pedagogy, integrative projects, and AI-supported learning, offering a robust model for preparing the next generation of digitally literate, creative, and adaptive professionals.

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