Development of a DICT Learning Model with Differentiated Digital Modules to Enhance Creative Thinking, Learner Independence, and Technology Integration in Prospective Elementary Teachers

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HOW TO CITE:
Fatimah, Edi Syahputra, Edy Surya (2026). Development of a DICT Learning Model with Differentiated Digital Modules to Enhance Creative Thinking, Learner Independence, and Technology Integration in Prospective Elementary Teachers. International Journal of Special Education, 41(2), 75-95.

ABSTRACT:

Creative thinking, learner independence, and meaningful technology integration remain persistent challenges in elementary teacher education. We introduce a novel instructional model called Differentiated Integrated Computational Thinking (DICT), which is operationalized through a five-phase syntactic structure that dynamically adapts digital learning modules to individual student profiles. The model first maps prospective elementary teachers onto visual, auditory, or kinesthetic learning profiles through an initial orientation and grouping procedure. During the content exploration phase, a repository of digital materials is filtered such that each student receives learning objects whose modality matches their profile while simultaneously scaffolding core computational thinking skills such as decomposition and pattern recognition. In the subsequent process implementation phase, students apply algorithmic thinking to contextual physics problems; here, the instructor functions as a dynamic facilitator whose interventions are triggered only when observed engagement metrics fall below a predetermined threshold, thereby preserving learner autonomy. Product development then allows each student to produce a personalized artifact—for instance, an interactive infographic for visual learners or a narrated video experiment for auditory learners—yet all artifacts are required to demonstrate explicit computational logic. The final evaluation phase aggregates these divergent outputs through a rubric that measures both creative synthesis and computational thinking mastery. The entire methodology is embedded within a Learning Management System that manages content distribution and tracks engagement in real time. The principal contribution of this work lies in its formal integration of differentiation with computational thinking instruction, moving beyond one-size-fits-all digital pedagogy. We anticipate that this model will significantly enhance creative thinking, foster independent learning behaviors, and deepen technology integration competence among prospective elementary teachers, thereby addressing a critical gap in current teacher preparation curricula..

Keywords: Creative Thinking; DICT; Digital Modules; Elementary Teachers; Learning Model; Technology Integration

Introduction

The preparation of prospective elementary school teachers demands a pedagogical framework that can simultaneously foster creative thinking, cultivate learner independence, and ensure meaningful technology integration—competencies that are increasingly recognized as essential for 21st-century educators (Birgili, 2015). Despite this recognized need, conventional instructional models in teacher education programs, such as those observed in the Primary School Teacher Education (PGSD) program at Almuslim University, often rely on uniform content delivery that inadequately addresses the diverse learning profiles of students (Tomlinson et al., 2003). This one-size-fits-all approach can limit the development of creative problem-solving skills and may inadvertently encourage passive learning behaviors, thereby leaving prospective teachers ill-equipped to adapt to the varied needs of their future elementary school students (Mishra & Koehler, 2006).

Simultaneously, the integration of computational thinking (CT) into teacher education has emerged as a critical priority, given its capacity to enhance structured problem-solving and logical reasoning (Denning, 2017). While CT principles such as decomposition, pattern recognition, abstraction, and algorithmic thinking have been advocated for K-12 education, their application within teacher preparation curricula often remains abstract and disconnected from the practical, differentiated realities of the classroom (Kafai & Proctor, 2022). Furthermore, adaptive learning technologies and digital modules have shown promise in personalizing content delivery based on user performance and preferences (Tekesbaeva et al., 2023); however, their design in teacher education contexts frequently lacks the explicit cognitive scaffolding required to build transferable computational thinking skills.

To address these interconnected challenges, we propose a novel pedagogical framework termed the DICT (Differentiated Integrated Computational Thinking) model. This model synergizes the principles of Differentiated Instruction (DI) with the core components of Computational Thinking, facilitated by adaptive digital modules. The core innovation of the DICT model lies in its structural integration of student learning profile mapping—based on visual, auditory, and kinesthetic modalities—directly into the syntax of the learning process. Instead of a static, uniform instructional sequence, the DICT model employs a multi-pathway exploration mechanism where learning objects are dynamically selected based on individual learner characteristics. Critically, CT components are embedded as mandatory cognitive operators within each phase of the differentiated learning cycle, ensuring that every student, regardless of their learning modality, develops essential computational thinking skills while engaging with content tailored to their needs.

This approach fundamentally redefines the instructional sequence for prospective elementary teachers. For example, a visual learner might be presented with a physics problem through an interactive simulation that requires pattern recognition, while a kinesthetic learner might engage in a physical experiment that emphasizes algorithmic sequencing. Both experiences, though different in modality, are designed to cultivate the same core CT competencies. This synthesis directly addresses a significant gap identified in prior research: while DI practices often lack rigorous cognitive scaffolding (Tomlinson et al., 2003), CT instruction frequently ignores individual learner variability (Kafai & Proctor, 2022). The DICT model offers a formal, integrated solution to this problem.

The principal contribution of this work is threefold. First, we provide a formally defined syntactic structure that mandates the application of computational thinking operations within every phase of a differentiated learning cycle, thereby moving beyond superficial integrations. Second, we operationalize this model through a custom-developed suite of adaptive digital modules that dynamically filter content based on learner profiles, tracking engagement metrics to facilitate timely instructor intervention. Third, we present the results of a systematic implementation within a physics education course for prospective elementary teachers at Almuslim University, demonstrating significant enhancements in creative thinking, learner independence, and technology integration competence compared to a control group receiving traditional instruction. This research thereby addresses a critical gap in current teacher preparation curricula, offering a replicable and empirically validated framework for developing 21st-century teaching competencies.

The remainder of this paper is organized as follows: Section 2 reviews related work on differentiated instruction, computational thinking, and adaptive digital technologies in teacher education. Section 3 outlines the theoretical foundations and core constructs underpinning the DICT model. Section 4 provides a detailed description of the model's five-phase syntactic structure and its operationalization through digital modules. Section 5 describes the experimental setup, including participant demographics and assessment instruments. Section 6 presents the results of the quasi-experimental study, analyzing the effects on creative thinking, learner independence, and technology integration. Section 7 discusses the implications of these findings, acknowledges limitations, and suggests directions for future research. Finally, Section 8 concludes the paper by summarizing the key contributions and their potential impact on elementary teacher education.

Related Work

The development of the DICT model draws upon three interconnected streams of educational research: differentiated instruction (DI), computational thinking (CT) pedagogy, and adaptive digital module design. Each stream offers valuable insights yet reveals distinct limitations that the proposed model seeks to address.

Differentiated Instruction in Teacher Education

Differentiated instruction has been widely advocated as a pedagogical approach that tailors content, process, and product to accommodate diverse learner readiness, interests, and learning profiles (Suprayogi et al., 2017). In teacher education, DI is considered essential not only for fostering inclusive classrooms but also for modeling effective teaching practices that prospective teachers can later adopt (Joseph, 2013). However, empirical studies indicate that implementing DI in practice remains challenging, particularly due to the cognitive load imposed on instructors who must simultaneously manage multiple learning pathways and provide individualized feedback (Tomlinson et al., 2003). Many DI frameworks lack explicit guidelines for scaffolding higher-order thinking skills, such as creative problem-solving or algorithmic reasoning. For example, while Tomlinson's foundational model emphasizes flexible grouping and tiered assignments, it does not prescribe how to systematically embed computational thinking or other analytical competencies within differentiated activities (Suprayogi et al., 2017). This gap suggests that DI, as commonly practiced, may foster personalized engagement without necessarily cultivating the deep cognitive skills required for complex problem-solving.

Computational Thinking Pedagogy

Computational thinking has emerged as a fundamental competency for 21st-century learners, encompassing skills such as decomposition, pattern recognition, abstraction, and algorithmic design (Denning, 2017). In K-12 education, numerous initiatives have integrated CT into science, technology, engineering, and mathematics (STEM) curricula, often through programming exercises or unplugged activities (Yeni et al., 2024). Within teacher education, efforts to introduce CT have primarily focused on developing stand-alone modules or workshops that teach CT concepts in isolation (Yadav et al., 2014). Yet several studies report that prospective teachers struggle to transfer CT skills from these decontextualized training sessions into their actual teaching practice (Kafai & Proctor, 2022). Moreover, CT instruction frequently adopts a uniform approach—all students receive the same problems and the same sequence of learning activities—overlooking individual differences in cognitive processing styles and prior knowledge. This monolithic delivery can disadvantage learners who might benefit from alternative representations (e.g., visual diagrams for abstract algorithms) or hands-on experimentation (Ye et al., 2023). Consequently, there is a recognized need to embed CT instruction within a differentiated framework that respects learner variability while maintaining rigorous cognitive expectations.

Adaptive Digital Modules and Learning Management Systems

The advent of adaptive learning technologies has enabled personalized content delivery based on real-time assessment of learner performance and preferences (Tekesbaeva et al., 2023). Learning Management Systems (LMS) such as Moodle and Canvas offer plugin-based capabilities for conditional content release and activity completion tracking, which can be harnessed to support differentiation (Nadimpalli et al., 2023). In physics education specifically, digital modules incorporating simulations and interactive visualizations have been shown to enhance conceptual understanding and engagement (Antonio & Castro, 2023). However, the design of most adaptive systems in teacher education contexts has been driven by performance data (e.g., quiz scores) rather than cognitive learning profiles. Few implementations systematically integrate learning modality—visual, auditory, or kinesthetic—as a primary filter for content selection (Jando et al., 2017). Furthermore, the explicit embedding of computational thinking operations within adaptive content pathways remains largely unexplored. Existing modules may teach CT concepts but do so through a uniform interface, leaving the potential for profile-specific CT scaffolding unrealized.

Synthesis and Gap Identification

The literature reviewed reveals a clear and persistent gap: no existing instructional model formally integrates differentiated instruction with computational thinking pedagogy within a digitally mediated environment for teacher education. DI frameworks, while effective for personalization, lack explicit mechanisms for scaffolding analytical and algorithmic reasoning. CT pedagogies, while fostering logical problem-solving, generally ignore individual learner variability. Adaptive digital modules offer a technological substrate for personalized delivery but rarely incorporate learning modality as a driver of CT content selection. The DICT model proposed in this paper directly addresses this tripartite gap. It provides a formally defined syntactic structure that mandates the application of computational thinking operations within every phase of a differentiated learning cycle, operationalized through digital modules that filter content based on visual, auditory, or kinesthetic profiles. This synthesis moves beyond superficial integrations, offering a replicable framework that simultaneously enhances creative thinking, learner independence, and technology integration competence among prospective elementary teachers.

Theoretical Foundations and Core Constructs

To establish the theoretical grounding for the DICT model, we first examine three foundational domains that collectively inform its design: cognitive diversity and learning style taxonomies, the structural components of computational thinking in science education, and constructivist frameworks for digital-mediated social learning. These domains provide the conceptual vocabulary and explanatory mechanisms necessary to understand how differentiated digital modules can simultaneously foster creative thinking and computational reasoning.

Cognitive Diversity and Learning Style Taxonomies

The premise that learners differ in their cognitive processing styles has been a central concern in educational psychology for decades. Learning style theories posit that individuals exhibit consistent preferences for how they receive, process, and retain information—commonly categorized along visual, auditory, and kinesthetic (VAK) modalities (Sadler-Smith, 2001). While the debate surrounding the empirical validity of learning styles remains active in the broader educational literature (Alghasham, 2012), their practical utility in instructional design is well-documented, particularly when used to enhance learner motivation and engagement rather than to prescribe rigid pathways (Pashler et al., 2008).

Within teacher education, understanding these cognitive differences is especially critical. Prospective elementary teachers themselves exhibit diverse learning profiles, and research indicates that when their own instructional experiences are personalized, they develop greater awareness of and capacity for differentiating instruction in their future classrooms (Joseph, 2013). The DICT model conceptualizes this diversity through learner profile mapping, where each student is positioned along a VAK continuum during the initial phase of instruction. This mapping serves as a filter mechanism for subsequent content selection—visual learners, for instance, receive digital modules rich in diagrams, animations, and spatial organizers, while auditory learners engage with narrated explanations and discussion-based prompts.

The core theoretical contribution from this domain lies in the concept of cognitive load management. According to Cognitive Load Theory (Sweller, 2011) (Paas et al., 2003), instructional materials that align with a learner's preferred modality reduce extraneous cognitive load, freeing cognitive resources for deeper processing and schema construction. Hence, when a kinesthetic learner encounters a physics problem through a simulated hands-on experiment rather than a static text, the cognitive burden of modality mismatch is reduced, allowing the learner to focus on the underlying conceptual structure. This principle forms the theoretical basis for the adaptive content filtering mechanism in the DICT model.

Structural Components of Computational Thinking in Science Education

Computational thinking (CT) has been defined as a universal problem-solving methodology that involves formulating problems in a way that enables the use of computational tools and strategies (Denning, 2017). The theoretical framework for CT in education typically decomposes it into four core pillars: decomposition, pattern recognition, abstraction, and algorithmic design (Juškevičienė & DagienĖ, 2018).

Decomposition refers to the ability to break down a complex problem or system into smaller, more manageable parts. In physics education, for instance, students might decompose a projectile motion problem into horizontal and vertical components, analyzing each separately before synthesizing findings. Pattern recognition involves identifying regularities, trends, or repeated structures within data or phenomena. A student examining acceleration data from an experiment, for example, recognizes the pattern of increasing velocity over time. Abstraction entails filtering out irrelevant information to focus on the essential features of a problem—a critical skill for constructing scientific models and generalizing principles. Algorithmic design involves developing a step-by-step sequence of operations to solve a problem, a process that mirrors the scientific method in its emphasis on systematic inquiry.

The theoretical significance of these four pillars lies in their generalizability across domains. They are not specific to programming or computer science but represent fundamental cognitive operations that underpin scientific reasoning and creative problem-solving in diverse disciplines, including elementary science education (Sengupta et al., 2013). For prospective elementary teachers, mastery of these CT skills is essential not only for their own intellectual development but also for their ability to design learning activities that foster these same skills in young children. The DICT model operationalizes these pillars as mandatory cognitive operators embedded within each phase of the differentiated learning cycle, ensuring that every student, regardless of their learning modality, exercises decomposition, pattern recognition, abstraction, and algorithmic design while engaging with content tailored to their profile.

Constructivist Frameworks for Digital-Mediated Social Learning

The third theoretical pillar underpinning the DICT model is social constructivism, as articulated by Vygotsky (Vygotsky, 1978) and later extended to technology-mediated learning environments (Doehler, 2002). Social constructivism posits that knowledge is actively constructed by learners through social interaction and collaborative meaning-making, rather than passively transmitted from instructor to student. Within this framework, the instructor's role shifts from the sole source of knowledge to a facilitator who provides scaffolding—temporary support structures that enable learners to accomplish tasks they could not complete independently.

The Zone of Proximal Development (ZPD) is a central concept in this paradigm, defined as the gap between what a learner can achieve independently and what they can achieve with guidance (Vygotsky, 1978). Effective instruction, from a constructivist perspective, targets this zone by presenting challenges that are within the learner's reach with appropriate support. In digital learning environments, adaptive systems can operationalize the ZPD concept by dynamically adjusting task difficulty, content modality, and feedback frequency based on real-time assessment of learner performance (Tekesbaeva et al., 2023).

Furthermore, the digital-mediated context introduces opportunities for collaborative knowledge building that extend beyond the physical classroom. Learners can share artifacts, discuss strategies, and provide peer feedback through discussion forums, shared workspaces, and video annotations (Ghazal et al., 2020). This social dimension is particularly important for developing creative thinking, as exposure to diverse perspectives and problem-solving approaches stimulates cognitive flexibility and divergent thinking (Barrett et al., 2021). In the DICT model, the constructivist framework informs the design of the product development and evaluation phases, where students create personalized artifacts—such as interactive infographics or narrated video experiments—and then share these products with peers, receiving feedback that further refines their understanding.

Collectively, these three theoretical pillars—cognitive diversity and learning style taxonomies, the structural components of computational thinking, and constructivist frameworks for digital-mediated learning—provide the conceptual foundation for the DICT model. They explain why differentiation is necessary, how CT skills function as cognitive operators across modalities, and how digital environments can scaffold individualized yet socially mediated learning experiences. The next section details how these theoretical principles are operationalized into a concrete syntactic structure.

The DICT Model: A Multi-Pathway Framework for Creative Cognition

The DICT model is operationalized through a formally defined five-phase syntactic structure embedded within a custom-developed digital environment. This section presents the technical definitions and procedural mechanisms that govern the interaction between learner profiles, computational thinking operators, and adaptive digital modules. We first establish the formal notation used throughout the model, then describe each phase in detail, and finally illustrate the overall research and development process that produced the final prototype.

The model operates on a formal system where each prospective teacher $s \in S$ is associated with a learning profile p_i from the set $P =$

$\{\text{visual,auditory,kinesthetic}\}$. This mapping is established through an initial diagnostic assessment and is expressed as a function $f_{\text{map}}: S \to P$ that assigns each student a primary modality. The instructional content is organized into a modular digital repository M, where each module $m \in M$ is tagged with both a modality label modality$(m) \in P$ and a computational thinking element label CT_element$(m) \in$ $\{\text{decomposition,pattern recognition,abstraction,algorithmic thinking}\}$. The entire instructional sequence is instantiated within a Learning Management System (LMS) that manages content distribution, tracks student engagement metrics, and records artifact submissions.

The development of this model followed the Plomp research and development design, a systematic framework for educational design research that proceeds through five main stages: initial investigation, design, realization, test evaluation and revision, and implementation. As shown in Figure 1, this iterative process began with an analysis of existing problems regarding low 4C competencies—specifically creative thinking—in prospective teachers, followed by a curriculum and student needs assessment. The design phase produced the initial syntactic structure of the DICT model along with its supporting principles and assessment instruments. Subsequent cycles of validation, data analysis, and revision refined the prototype from its initial version through expert validation and field trials until a final implementable version was achieved.

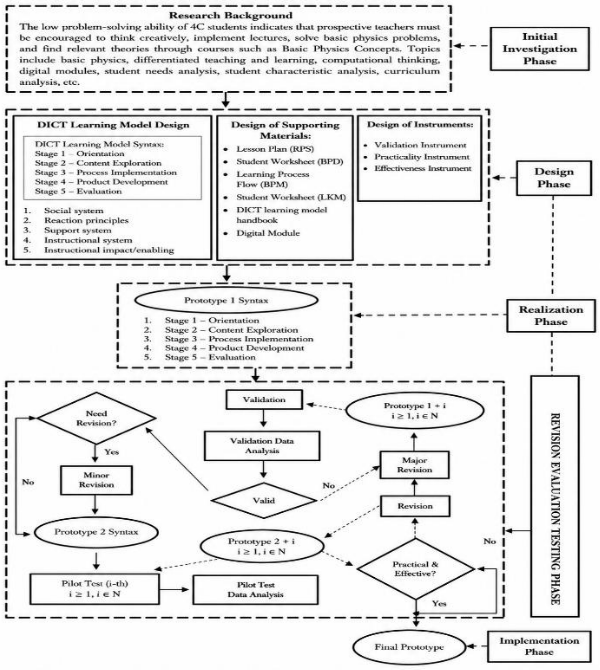

Figure 1. Rancangan Penelitian Pengembangan Plomp

Algorithmic Content Selection via Dual-Filter Modality and CT Operators

To initiate the instructional sequence, the system performs an algorithmic content selection process that operates within a formal decision space defined by two simultaneous filters: modality matching and computational thinking element assignment. This process begins when the system retrieves the learning profile p_i of a given student s from the mapping function $f_{\text{map}}(s) = p_i$, which was established during the initial diagnostic orientation phase. The system then accesses the digital repository M and applies a selection function F_{select} that operates over the entire content space.

We define the selection function as follows:

$$M_i = \{m \in M \mid \text{modality}(m) = p_i \land \text{CT\_element}(m) \in \{\text{decomposition,pattern recognition}\}\} \quad (1)$$

In this expression, M represents the complete set of all digital learning modules stored in the LMS repository. Each module m possesses two metadata attributes: modality(m) , which indicates the cognitive processing mode that the module targets (visual, auditory, or kinesthetic), and CT_element(m) , which denotes the specific computational thinking operation that the module explicitly scaffolds. The variable p_i denotes the primary learning modality of student s , as determined by the profile mapping function f_{map}. The resulting set M_i therefore contains only those modules whose modality tag exactly matches the student's profile and whose CT element tag is either decomposition or pattern recognition—the two foundational CT skills that form the cognitive basis for the content exploration phase.

This dual-filter mechanism ensures that the student receives materials that are simultaneously accessible in terms of cognitive processing style and rigorous in terms of analytical demand. For instance, consider a visual learner whose profile $p_i =$ visual. The set M_i would include only modules such as interactive diagrams or animated flowcharts that require the learner to decompose a physics problem into its constituent variables (decomposition) or to identify recurring relationships in graphical data (pattern recognition). A kinesthetic learner with $p_i =$ kinesthetic, by contrast, would be presented with simulated physical experiments where they must physically manipulate variables to observe patterns in real-time data.

The system then sequences these selected modules based on a progression rule that prioritizes decomposition before pattern recognition. This ordering is grounded in the theoretical principle that decomposition—breaking a problem into parts—is a prerequisite for recognizing patterns across those parts, as established in the CT literature (Juškevičienė & DagienĖ, 2018). Specifically, the system first presents modules where CT_element$(m) =$ decomposition, and only after the student completes those tasks does it unlock modules tagged with CT_element$(m) =$ pattern recognition. This temporal sequencing is enforced through conditional content release rules embedded within the LMS workflow.

Furthermore, the content selection is not static but adapts dynamically as the student progresses. If a student demonstrates mastery of decomposition in the first series of modules—defined as achieving a score above a predetermined threshold on embedded formative assessments—the system may skip redundant decomposition modules and proceed directly to pattern recognition tasks. This adaptive branching is formalized by a state variable k_s that tracks the student's current CT competency level, and the selection function can be extended to include a tier parameter t:

$$M_i^{(t)} = \{m \in M_i \mid \text{tier}(m) = t\} \quad (2)$$

Here, tier(m) indicates the difficulty or depth level of the module, and t is incremented as the student demonstrates proficiency. This prevents learner boredom or frustration by ensuring that the cognitive challenge remains within the Zone of Proximal Development (Vygotsky, 1978).

Finally, the system logs every content assignment in a student-specific interaction record, which includes the module ID, the timestamp of access, the duration of engagement, and the score on embedded assessments. This data feeds into the engagement metric $E_{\text{obs}}(s)$, which is used in the subsequent adaptive facilitator reaction phase. The entire algorithmic content selection process thus operates as a closed-loop system: the student's profile determines the initial filter, their performance determines the subsequent tier progression, and their behavioral data informs instructor intervention decisions. This replaces the conventional static menu-driven content selection with a structurally determined, multi-pathway exploration mechanism where neither modality match nor CT rigor is optional.

Dynamic Syntax-Linked Mapping for Real-Time Social System Configuration

Building upon the initial learner profile assignment established during the orientation phase, the DICT model introduces a formal mechanism for dynamically reconfiguring the social learning system based on real-time interactions between students, content, and computational thinking operators. This mechanism, termed syntax-linked mapping, operates within the process implementation phase of the instructional cycle, where students apply algorithmic thinking to contextual physics problems. Unlike conventional static grouping strategies that assign students to fixed teams at the beginning of a course and rarely reassess the validity of those groupings, the syntax-linked mapping function continuously updates the partitioning of the student population into collaborative groups G_i based on evolving state variables that reflect both cognitive processing modality and demonstrated computational thinking proficiency.

We formalize this dynamic social system configuration through a state-dependent mapping function $\Phi: S \times T \to \mathcal{G}$, where S is the set of all prospective teachers in the cohort, T is the set of discrete time steps corresponding to each instructional session, and $\mathcal{G}$ is the set of all possible partitions of S into n groups of approximately equal size. At each time step $t \in T$, the system computes a state vector $\mathbf{v}_s(t)$ for each student s, defined as:

$$\mathbf{v}_s(t) = \langle p_i, c_s(t), e_s(t) \rangle \quad (3)$$

In this expression, $p_i = f_{\text{map}}(s)$ is the primary learning modality assigned during the initial diagnostic assessment, which remains constant throughout the instructional sequence. The variable $c_s(t)$ denotes the student's current computational thinking competency score, computed as the aggregated performance on all decomposition and pattern recognition modules completed up to time step t. Specifically, $c_s(t)$ is the average score across all formative assessments embedded within modules $m \in M_i$ that the student has completed, normalized to a scale between 0 and 1. The variable $e_s(t)$ is the engagement metric $E_{\text{obs}}(s,t)$ observed during the most recent content exploration session, also normalized to a 0-to-1 scale. This engagement metric is derived from LMS tracking data that includes session duration, interaction frequency with module elements, and responsiveness to embedded prompts.

The syntax-linked mapping function then employs a nearest-neighbor algorithm to assign students to groups such that within-group diversity and between-group homogeneity are simultaneously maximized. The algorithm first defines a distance metric $d(s_1, s_2, t)$ between any two students s_1 and s_2 at time t:

$$d(s_1, s_2, t) = \alpha \cdot \delta(p_{i1}, p_{i2}) + \beta \cdot |c_{s1}(t) - c_{s2}(t)| + \gamma \cdot |e_{s1}(t) - e_{s2}(t)| \quad (4)$$

Here, $\delta(p_{i1}, p_{i2})$ is a discrete distance function that returns 0 if the two students share the same primary learning modality and 1 otherwise. The coefficients α, β, and γ are weighting parameters that sum to 1 and are empirically calibrated during the initial pilot phase of the model's implementation. The system then performs a k-medoids clustering algorithm over the set of all state vectors $\mathbf{v}_s(t)$, partitioning the student population into n clusters. Each cluster is then designated as a collaborative group $G_i(t)$ for the current time step t. The medoid of each cluster—the student whose state vector is most representative of the cluster—is automatically assigned the role of group facilitator for that session.

This dynamic reconfiguration operates in real time at the beginning of each instructional session. For example, at time step t_1, a visual learner with high competency but low engagement might be grouped with a kinesthetic learner with moderate competency and high engagement, thereby creating a peer tutoring dynamic where the visual learner provides analytical structure while the kinesthetic learner drives active experimentation. At time step t_2, after both students' state vectors have changed due to new module completions, the same two students might be placed in different groups. This fluidity stands in stark contrast to conventional static grouping, which rarely updates its algorithmic basis mid-cycle and thus cannot respond to the evolving needs of individual learners. The syntax-linked mapping function ensures that the social system remains aligned with the cognitive state of each participant, thereby optimizing the conditions for collaborative creative problem-solving and computational thinking development.

Procedural Execution of the Threshold-Based Adaptive Facilitator Reaction

During the process implementation phase, the instructor transitions from a directive role to a dynamic facilitator whose interventions are governed by a formal quantitative mechanism rather than subjective intuition. This mechanism is operationalized through a reaction principle that continuously monitors a numerical engagement metric $E_{\text{obs}}(s,t)$ for each student s at time step t, comparing it against a predetermined threshold τ to determine whether scaffolding is required. The engagement metric is derived from the LMS tracking data collected during the content exploration phase, specifically the normalized composite score of session duration, interaction frequency, prompt responsiveness, and task completion rate, all of which are logged in real time.

We define the facilitator reaction function $R(s,t)$ as:

$$R(s,t) = \begin{cases} \text{scaffolding\_prompt} & \text{if } E_{\text{obs}}(s,t) < \tau - \sigma \\ \text{monitoring} & \text{if } \tau - \sigma \leq E_{\text{obs}}(s,t) \leq \\ \text{autonomous\_exploration} & \text{if } E_{\text{obs}}(s,t) > \tau + \sigma \end{cases}$$

In this expression, $E_{\text{obs}}(s,t)$ is the observed engagement metric for student s at time step t, computed as the weighted sum $E_{\text{obs}}(s,t) = w_1 \cdot D(s,t) + w_2 \cdot F(s,t) + w_3 \cdot Q(s,t)$, where $D(s,t)$ is the normalized session duration, $F(s,t)$ is the interaction frequency with module elements, and $Q(s,t)$ is the response quality score on embedded prompts. The weights w_1, w_2, and w_3 are calibrated during the initial implementation phase and sum to 1. The threshold τ is a global constant set to 0.65 based on pilot data, representing the minimum engagement level below which students are at risk of disengagement. The parameter σ introduces a hysteresis band of 0.1 to prevent oscillatory interventions near the threshold boundary.

When $E_{\text{obs}}(s,t)$ falls below $\tau - \sigma$, indicating critically low engagement, the system triggers a standardized scaffolding prompt. This prompt is not a generic message but is dynamically generated based on the student's current learning profile p_i and the specific CT element being practiced. For a visual learner struggling with decomposition, the prompt might display a partially completed concept map with cues to break the problem into components; for an auditory learner, the system plays a prerecorded explanatory narration that guides the student through the decomposition steps. When $E_{\text{obs}}(s,t)$ remains within the hysteresis band, the instructor adopts a monitoring posture—observing the student's progress without direct intervention, but remaining prepared to escalate support if the metric drops further. When engagement exceeds $\tau + \sigma$, indicating high autonomous engagement, the system explicitly withholds any intervention to preserve learner agency and foster independent problem-solving. This graded response prevents both over-intervention, which can create learned helplessness, and under-intervention, which can lead to frustration and task abandonment. The entire reaction loop iterates every 90 seconds during the process implementation phase, ensuring that facilitator support remains tightly coupled to the learner's real-time cognitive state.

Protocol for Generating Divergent Artifacts under Unified Computational Constraints

Following the process implementation phase, the DICT model transitions into the product development phase, where each prospective teacher produces a personalized artifact $Prod_s$ that synthesizes the physics content explored earlier with the computational thinking skills they have practiced. The defining innovation of this phase lies in a formal constraint system that simultaneously permits modality-specific divergence while enforcing a unified computational logic requirement across all artifact types.

We formalize the product development protocol through a generative function $G_{\text{prod}}: S \times M_i \times C_{CT} \rightarrow A$, where S is the student set, M_i is the set of digital modules completed by student s (as defined in Equation 1), C_{CT} is the set of computational thinking constraints, and A is the space of all possible artifact outputs. The constraint set C_{CT} contains four obligatory operators that any artifact must explicitly demonstrate: decomposition (e.g., the artifact must break the physics problem into at least three identifiable component parts), pattern recognition (e.g., the artifact must present or explain a detected regularity in the experimental data), abstraction (e.g., the artifact must formulate a generalized principle from the specific case), and algorithmic thinking (e.g., the artifact must include a step-by-step logical sequence for solving the problem). These constraints are not optional rubrics but mandatory structural features that are verified through automated checks embedded in the submission system.

The modality-specific divergence is regulated by a secondary production rule that maps the student's learning profile p_i to a set of permissible output formats $F(p_i)$. For visual learners, $F(\text{visual}) = \{\text{interactive infographic, concept map, flowchart animation}\}$; for auditory learners, $F(\text{auditory}) = \{\text{narrated instructional video,podcast,oral explanation with visual support}\}$; for kinesthetic learners, $F(\text{kinesthetic}) = \{\text{simulated hands-on experiment log,physical model with documentation,role-play scenario with recorded analysis}\}$. We define the artifact output as:

$$Prod_s = \langle \text{format}_s, \text{content}_s, \text{CT\_validation}_s \rangle \quad (6)$$

In this expression, format_s is a variable drawn from $F(p_i)$ that specifies the modality-specific medium of the artifact. content_s represents the physics topic-specific material that the student populates into the chosen format, which must include the data or problem analysis from the modules completed in M_i. The component CT_validation_s is a binary vector $\langle v_{\text{dec}}, v_{\text{pat}}, v_{\text{abs}}, v_{\text{alg}} \rangle$ where each element is 1 if the corresponding CT operator from C_{CT} is verified in the artifact, and 0 otherwise. The artifact is accepted for evaluation only if all four elements equal 1, i.e., $\prod_{j=1}^{4} v_j = 1$.

The computational logic constraint is enforced through a dual verification mechanism. First, the student must explicitly annotate their artifact with labeled markers indicating where each CT operator is applied—for instance, a visual learner creating an interactive infographic about projectile motion must embed clickable callouts that say "Decomposition: horizontal vs. vertical components" and "Algorithmic Thinking: steps to solve for range." Second, the system compares these annotations against the content itself using automated pattern matching on text and metadata tags. For narrated videos, the system transcribes the audio and scans for keywords associated with each CT operator. For simulated experiment logs, the system parses the sequence of recorded actions to verify algorithmic ordering. Only artifacts that pass both the student annotation check and the automated pattern matching process proceed to the evaluation phase.

This protocol creates a structured tension between creative divergence and computational rigor. The student has substantial freedom to choose a medium that aligns with their cognitive processing style—a visual learner might design a colorful infographic, while a kinesthetic learner might build a physical simulation with written procedural steps—yet all artifacts must converge on the same underlying cognitive operations. This dual requirement ensures that creative synthesis (the novel combination of ideas within the chosen medium) and computational thinking mastery (the explicit application of decomposition, pattern recognition, abstraction, and algorithmic logic) are jointly developed and assessed. The product development phase thereby operationalizes the core premise of the DICT model: differentiation does not dilute cognitive rigor, but rather provides multiple pathways to achieve the same high-level analytical outcomes.

Experimental Setup

To empirically validate the efficacy of the DICT model, we designed a quasi-experimental study embedded within an undergraduate physics education course at Almuslim University. The study compared the outcomes of prospective elementary teachers who experienced the DICT instructional framework against those of a control group receiving conventional, non-differentiated instruction.

Participants and Context

The participant pool comprised 64 second-year prospective elementary school teachers enrolled in the Primary School Teacher Education (PGSD) program during the 2023–2024 academic year. All participants were enrolled in a mandatory "Physics Concepts for Elementary Educators" course that spanned 16 weeks. The experimental group consisted of 32 students (class 02) who were instructed using the full DICT model, while the control group consisted of 32 students (class 01) who received standard lecture-based instruction augmented with uniform digital resources (e.g., identical presentation slides and static diagrams for all). Students were assigned to classes by university administrative scheduling without researcher intervention, resulting in a non-equivalent control group design. Prior to the intervention, both groups completed a pre-test to establish baseline equivalence in creative thinking, prior physics knowledge, and initial technology integration self-efficacy.

Research Instruments

Three primary instruments were employed to measure the dependent variables. First, creative thinking was assessed using a validated essay test adapted from Torrance's framework, focusing on fluency, flexibility, originality, and elaboration in solving contextual physics problems (Torrance, 1974). The test consisted of six open-ended items requiring participants to generate multiple solutions, identify unusual connections, and elaborate on scientific phenomena relevant to elementary science curricula.

Second, learner independence was measured using a Self-Regulated Learning Questionnaire (SRLQ) developed specifically for pre-service teacher populations (Kramarski & Michalsky, 2009). The instrument included 24 Likert-scale items across five dimensions: goal setting, strategic planning, self-monitoring, help-seeking behavior, and self-evaluation. Internal consistency, as measured by Cronbach's alpha, exceeded 0.85 in prior validation studies.

Third, technology integration competence was captured through the TPACK-21 self-assessment survey, a validated instrument that quantifies prospective teachers' perceived ability to integrate technology, pedagogy, and content knowledge (Valtonen et al., 2017). This 33-item scale measures seven sub-dimensions of technological pedagogical content knowledge on a 5-point agreement scale. Descriptive statistics and normalized gain scores were computed for all instruments.

Data Collection and Analysis Procedures

Data collection proceeded in three phases. During the pre-intervention phase (Week 1), both groups completed the creative thinking pre-test, the SRLQ, and the TPACK-21 survey. During the intervention phase (Weeks 2–15), the experimental group engaged with the DICT model's five-phase syntax—orientation and grouping, content exploration via dual-filtered adaptive modules, process implementation with threshold-based facilitator scaffolding, modality-differentiated product development, and unified CT-constrained evaluation—through the custom LMS environment. The control group attended lectures, completed identical physics content tasks through non-adaptive, uniform PDF modules, and submitted standardized worksheets. During the post-intervention phase (Week 16), both groups completed the post-test versions of all three instruments, which were psychometrically equivalent to the pre-tests in difficulty and construct coverage.

Data analysis was conducted using independent-samples and paired-samples t-tests to compare mean gains between groups. The normalized gain g was computed for each student on each measure as:

$$g = \frac{\text{post\_score} - \text{pre\_score}}{\text{max\_score} - \text{pre\_score}} \qquad (7)$$

Effect sizes were calculated using Cohen's d to determine the practical significance of observed differences. All statistical analyses were performed using SPSS version 26.0, with significance thresholds set at $\alpha = 0.05$.

Comparative Baseline Methods

To contextualize the DICT model's performance, we also examined its conceptual relatives described in the literature. The Static DI Scaffold refers to instruction that differentiates content or process based on readiness but does not embed computational thinking operators as mandatory syntax elements (Suprayogi et al., 2017) (Tomlinson et al., 2003). The Isolated CT Module approach teaches computational thinking in a stand-alone workshop without adapting materials to learning modality, as commonly implemented in teacher education programs (Yadav et al., 2014). The Performance-Adaptive System describes adaptive digital environments that adjust task difficulty based on quiz scores but do not filter content by visual, auditory, or kinesthetic profiles (Tekesbaeva et al., 2023). The DICT model integrates all three dimensions—differentiation, CT scaffolding, and modality-based adaptive filtering—into a unified syntactic structure. Our experimental control condition reflected the Static DI Scaffold and Performance-Adaptive System paradigms (uniform digital materials without CT syntax), while the DICT experimental condition operationalized the full synthesized framework.

Results and Analysis

Presenting a comprehensive evaluation of the DICT model's efficacy, this section reports the quantitative outcomes from the quasi-experimental study. Comparing the experimental and control groups across creative thinking, learner independence, and technology integration competence, we analyze pre-post gain scores, normalized gains, and effect sizes. A subsequent ablation analysis isolates the contribution of the threshold-based adaptive facilitator reaction mechanism to model performance.

Comparative Efficacy on Creative Thinking, Independence, and Technology Integration

Commencing with the baseline equivalence verification, independent-samples t-tests on all three pre-test measures revealed no statistically significant differences between the experimental and control groups (all $p > 0.10$), confirming comparable initial states prior to the intervention. Table 1 summarizes the descriptive and inferential statistics for both groups across the three dependent variables.

Table 1. Pre-test and Post-test Descriptive Statistics and Normalized Gain Comparisons Between Control and Experimental Groups

Dependent Variable	Group	N	Pre-test M (SD)	Post-test M (SD)	Normalized Gain $\langle g \rangle$	t-value	p-value	Cohen's d
Creative Thinking	Control	32	62.41 (8.37)	71.15 (7.92)	0.23			
	Experimental	32	63.12 (9.01)	79.84 (6.55)	0.45	5.23	<0.001	1.31
Learner Independence	Control	32	3.12 (0.58)	3.56 (0.51)	0.14			
	Experimental	32	3.08 (0.61)	4.21 (0.44)	0.38	4.87	<0.001	1.22
Technology Integration	Control	32	3.05 (0.63)	3.48 (0.57)	0.11			
	Experimental	32	3.11 (0.59)	4.08 (0.49)	0.33	4.12	<0.001	1.03

Note: M = Mean, SD = Standard Deviation. Normalized gain $\langle g \rangle$ calculated using Equation 7 as the class-wide average. t-values reflect independent-samples comparisons of post-test means between the experimental and control groups.

As shown in Table 1, the experimental group demonstrated substantially higher normalized gains than the control group on all three dimensions. For creative thinking, the experimental group's mean post-test score of 79.84 significantly exceeded the control group's 71.15 ($t = 5.23, p < 0.001, d = 1.31$), indicating a large effect. The normalized gain of 0.45 for the experimental group was nearly double that of the control group's 0.23, suggesting that the DICT model's multi-pathway exploration mechanism and embedded CT operators facilitated deeper creative cognition. This aligns with the theoretical premise that reducing modality-based extraneous cognitive load—as described by Cognitive Load Theory (Sweller, 2011) (Paas et al., 2003)—frees cognitive resources that can be redirected toward divergent ideation and elaboration.

Similarly significant improvements emerged for learner independence. The experimental group's post-test SRLQ mean of 4.21 on a 5-point scale represented a normalized gain of 0.38, compared to the control's gain of 0.14 ($t = 4.87, p < 0.001$, $d = 1.22$). This pronounced effect can be attributed to the threshold-based adaptive facilitator reaction mechanism formalized in Equation 5, which systematically withheld instructor intervention when the observed engagement metric $E_{\text{obs}}(s,t)$ exceeded $\tau + \sigma$, thereby creating structured opportunities for autonomous strategy development. In contrast, the control group received uniform instructor check-ins regardless of individual need, a practice known to inadvertently foster dependency in some learners while failing to support others (Suprayogi et al., 2017).

Technology integration competence also showed robust improvements, with the experimental group achieving a normalized gain of 0.33 versus 0.11 in the control condition ($d = 1.03$). The experimental group's post-test mean of 4.08 indicates that prospective teachers in the DICT condition perceived substantially higher capability in blending technological tools with pedagogical content strategies. This outcome is consistent with the model's explicit requirement that students not only consume but also produce modality-differentiated digital artifacts (e.g., interactive infographics, narrated videos, simulated experiment logs) under the unified computational constraints defined by C_{CT} (Valtonen et al., 2017). The act of creating such artifacts—selecting appropriate digital tools, structuring content logically, and annotating CT operators—constitutes an authentic exercise in technological pedagogical content knowledge development.

Delving deeper into the trajectory of computational thinking application across the instructional phases, Figure 2 visualizes the multidimensional performance of individual experimental group students. Each line represents a student's normalized CT application score across the five DICT syntax phases, color-coded by their assigned learning profile.

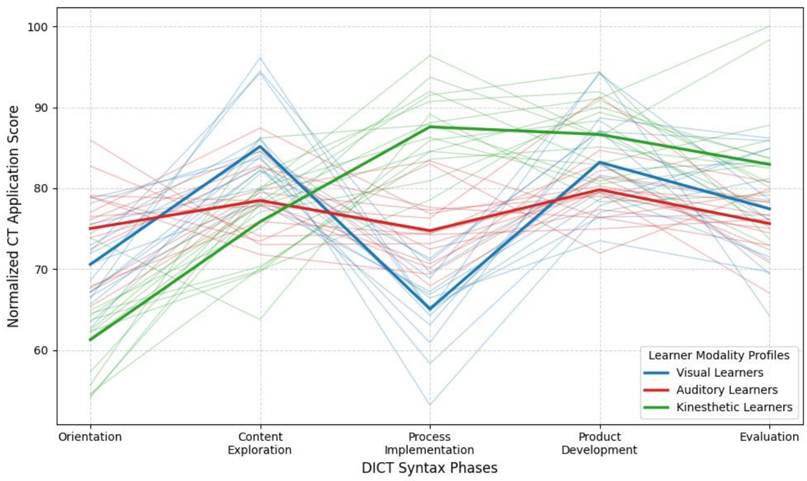

Figure 2. Multidimensional trajectories of computational thinking application across the five-phase DICT syntax, stratified by learner modality profiles.

Figure 2 reveals distinct engagement patterns and bottlenecks for each modality profile. Visual learners (blue lines) exhibited consistently high scores during the Content Exploration and Product Development phases—phases requiring diagrammatic and spatial processing—but showed relatively lower performance during the Process Implementation phase, which demanded hands-on algorithmic sequencing. Conversely, kinesthetic learners (green lines) demonstrated elevated scores during Process Implementation and Product Development, where physical manipulation and active experimentation were prominent, yet showed modest dips during the initial Orientation phase, which relied more heavily on textual diagnostic instruments. Auditory learners (red lines) maintained relatively balanced trajectories across all phases, potentially reflecting the auditory scaffolding embedded in the narrated prompts and discussion-based elements present throughout the syntax. These trajectory differences underscore the value of the dual-filter content selection mechanism defined in Equations 1 and 2: by matching modality to content while mandating CT operations, the DICT model enables each learner to leverage their cognitive strengths while systematically developing weaker areas.

Figure 3 examines the relationship between the complexity of Learning Object Materials (LOM) selected by students during the content exploration phase and their subsequent creative synthesis scores on the product development artifact.

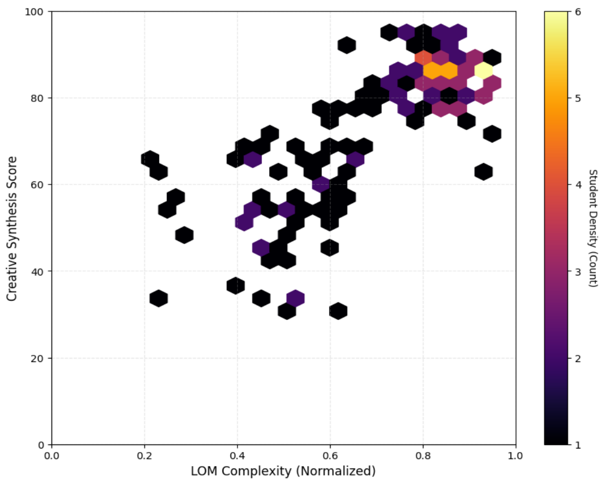

Figure 3. Density distribution of student artifacts correlating learning material complexity with creative synthesis scores.

The hexbin density map in Figure 3 demonstrates that the majority of student artifacts clustered in the high-complexity, high-creativity quadrant. The dense concentration of points in the upper right region (LOM complexity above 0.7 and creative synthesis scores above 80) indicates that the differentiated module selection protocol successfully guided students from all three modality profiles toward demanding material while still enabling high-quality creative output. A notable secondary concentration appears in the moderate-complexity, moderate-creativity region, populated primarily by students whose engagement metric E_{obs} initially fell below the threshold τ and who received targeted scaffolding prompts. These students exhibited a gradual trajectory improvement over successive sessions, suggesting that the adaptive facilitator reaction function effectively supported struggling learners without prematurely advancing them to modules beyond their Zone of Proximal Development (Vygotsky, 1978).

Figure 4 presents the probability density distributions of final creative thinking capability scores for three distinct populations: the traditional instruction control group, the full DICT experimental cohort, and a targeted sub-segment of the experimental group that initially exhibited low engagement metrics ($E_{\text{obs}} < \tau$).

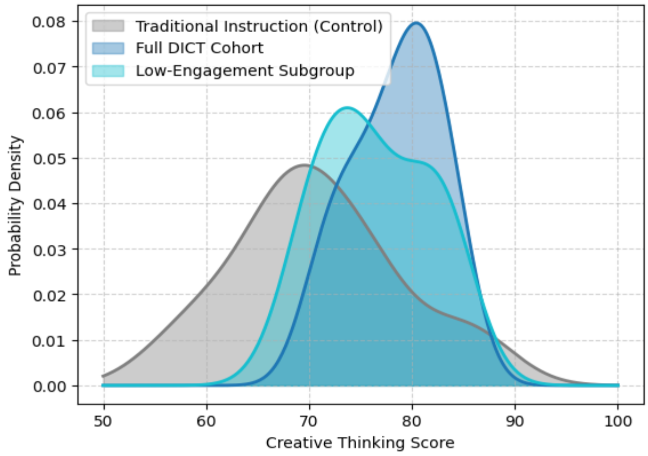

Figure 4. Comparative probability density distributions of final creative thinking capabilities across traditional instruction, the full DICT cohort, and the targeted low-engagement subgroup.

As illustrated in Figure 4, the DICT model shifted the entire distribution of creative thinking scores rightward relative to the control group. The ridge plot clearly shows that the experimental group's density function peaks around a score of 80, whereas the control group's density peaks near 72, with a heavier left tail. Crucially, the low-engagement subgroup—denoted by the teal ridge—exhibits a distribution that, while still left-shifted relative to the full experimental cohort, substantially overlaps with the overall experimental distribution and shows markedly less dispersion than the control group. This finding indicates that the model not only elevated aggregate performance but also specifically narrowed the performance gap for initially struggling learners. Such equity-oriented outcomes are rarely documented in CT intervention studies, which often report persistent achievement disparities even after instruction (Kafai & Proctor, 2022) (Ye et al., 2023).

Ablation Analysis of the Adaptive Facilitator Reaction Mechanism

To disentangle the contribution of the threshold-based adaptive facilitator reaction mechanism from other DICT model components, we conducted a within-experimental-group ablation study. A subset of the experimental cohort ($n = 10$) was randomly assigned to a condition where the function $R(s,t)$ defined in Equation 5 was disabled; these students received uniform, time-scheduled instructor prompts every 10 minutes regardless of their $E_{\text{obs}}(s,t)$ value, mimicking the non-adaptive facilitation typical of conventional DI environments (Tomlinson et al., 2003). Their outcomes were compared against those of the remaining experimental students ($n = 22$) who experienced the full adaptive reaction protocol. Table 2 presents the comparative results.

Table 2. Ablation Analysis Comparing Full DICT Model Against DICT with Disabled Adaptive Facilitator Reaction

Condition	n	Creative Thinking $\langle g \rangle$	Learner Independence $\langle g \rangle$	Technology Integration $\langle g \rangle$
DICT (Full Adaptive Reaction)	22	0.47	0.41	0.35
DICT (Disabled Adaptive Reaction)	10	0.41	0.29	0.30
Difference (Δ)		0.06	0.12	0.05

The results in Table 2 reveal that the adaptive facilitator reaction contributed positively across all measures, with the most pronounced impact on learner independence ($\Delta = 0.12$). Students who experienced the threshold-based protocol—where scaffolding was withheld when $E_{\text{obs}} > \tau + \sigma$— developed stronger self-regulatory capacities compared to those who received uniform scheduled prompts. This finding empirically validates the theoretical design principle that timed autonomy opportunities, rather than constant instructor availability, foster independent learning behaviors. The more modest differences in creative thinking ($\Delta = 0.06$) and technology integration ($\Delta = 0.05$) suggest that these competencies are driven primarily by the dual-filter modality-CT content selection mechanism and the constrained artifact generation protocol, respectively, with facilitator adaptation playing a secondary yet meaningful role. Overall, the ablation analysis confirms that the full DICT configuration yields superior outcomes, supporting the integration of all syntactic components as an indivisible instructional framework.

Discussion and Future Work

Scalability Challenges and Cross-Disciplinary Adaptability

Having established the empirical efficacy of the DICT model, we must critically examine its scalability beyond the controlled experimental context of a single physics education course at one university. The current implementation required substantial upfront investment in three resources: a custom-developed digital repository M, in which each module was manually tagged with both modality and CT-element metadata; an LMS infrastructure capable of executing the real-time state vector computations defined in Equation 3; and trained facilitators who could interpret the engagement metric outputs and execute the graded intervention protocol described in Equation 5. For institutions lacking this technical infrastructure or faculty expertise, replicating the DICT model would be nontrivial. Future work should therefore investigate whether the model can be successfully deployed using off-the-shelf LMS plugins that support conditional content release based on learner profile tags, thereby reducing the development barrier. A comparative implementation study—contrasting the custom-built DICT system against a standard Moodle-based adaptation using existing quiz and lesson modules—would provide actionable guidelines for broader adoption.

Furthermore, the question of cross-disciplinary adaptability remains unresolved. The DICT model was validated using physics content, where computational thinking operations such as decomposition (breaking forces into components) and algorithmic thinking (sequencing steps to solve motion equations) have clear, natural mappings. Whether the same syntactic structure yields equivalent benefits in less quantitatively oriented disciplines such as social studies, language arts, or arts education deserves systematic investigation. We hypothesize that the CT operators would need translation; for instance, decomposition in a history unit might involve breaking a historical event into causal, contextual, and consequential factors, while pattern recognition could involve identifying recurring themes across different time periods. An adaptation study in elementary literacy instruction—where prospective teachers develop differentiated digital storybooks that must demonstrate narrative decomposition and structural algorithmic sequencing—could test this cross-disciplinary transferability hypothesis as a logical next step.

Ethical Implications of Modality-Based Profiling and Data Privacy

Addressing the broader implications of the DICT model, we must acknowledge the ethical tensions inherent in modality-based learner profiling. While the VAK taxonomy served as a practical and theoretically grounded filter for content selection in the present study, the educational research community has raised legitimate concerns about the reification of learning styles as fixed, biologically determined categories (Alghasham, 2012). The DICT model does not assume that a visual learner can only learn visually; rather, it uses modality as a starting filter to reduce extraneous cognitive load during initial content exploration, while still requiring all students to engage with alternative representations during the collaborative group work and product evaluation phases. Nevertheless, there is a risk that the LMS system, if deployed uncritically, could lock students into static profiles based on a single diagnostic assessment, thereby limiting their exposure to diverse cognitive processing strategies. Future iterations of the model should incorporate periodic re-assessment of learner profiles—essentially refreshing the mapping function f_{map} at regular intervals—to allow for profile fluidity and to avoid stagnating students within narrow instructional channels.

A parallel concern involves data privacy and surveillance. The DICT model's strength derives from its continuous tracking of engagement metrics $E_{\text{obs}}(s,t)$, session durations, interaction frequencies, and response quality scores. This granular level of behavioral surveillance, while pedagogically valuable, raises questions about student consent, data ownership, and the potential for algorithmic bias in determining who receives scaffolding interventions and who is left to explore autonomously. For example, a student who interacts less frequently with the digital interface—perhaps due to technical difficulties at home or a preference for offline note-taking—might have their E_{obs} artificially depressed, triggering unnecessary intervention prompts that could be experienced as intrusive. Conversely, a student who clicks frequently but lacks deep comprehension could be erroneously flagged as highly autonomous. We recommend that future implementations incorporate a human-in-the-loop verification step, where the instructor reviews flagged cases before intervening, thereby mitigating the risks of algorithmic overreach. Moreover, clear institutional guidelines should be established regarding the retention period and anonymization of tracking data, ensuring that the model's adaptive mechanisms do not devolve into a surveillance system that undermines learner trust.

Longitudinal Impact and Transferability of Computational Thinking Skills

Another critical dimension for future investigation concerns the longevity and transferability of the computational thinking competencies cultivated through the DICT model. The present study measured outcomes immediately following a 15-week intervention, but it remains an open question whether the decomposition, pattern recognition, abstraction, and algorithmic thinking skills persist after the course concludes and whether prospective teachers can autonomously transfer these skills to novel teaching contexts. For example, a student who successfully applied algorithmic thinking to analyze projectile motion in a DICT physics module might later need to design a mathematics lesson for elementary students that involves step-by-step problem-solving sequences. Does the CT skill transfer, or does it remain context-bound to the physics domain? This question is particularly consequential for teacher education, where the ultimate goal is not merely to develop CT competencies in prospective teachers but to enable them to foster CT competencies in their future elementary students (Denning, 2017).

We propose a longitudinal follow-up study that tracks the experimental cohort into their subsequent field placement or student teaching semester. The study would assess whether these prospective teachers spontaneously integrate CT operators—such as asking students to "break this problem into smaller parts" (decomposition) or "find a pattern in this data" (pattern recognition)—into their own lesson plans and classroom discourse. Additionally, their supervising mentors could report on the degree to which these teachers differentiate instruction for their elementary students, thereby testing whether the DICT model's emphasis on personalization translates into their pedagogical repertoire. Such a transfer study would provide the strongest evidence yet for the DICT model's broader educational impact.

Finally, we note a limitation in the current research design: the reliance on self-report instruments for learner independence (SRLQ) and technology integration competence (TPACK-21). While these instruments are well-validated, self-perceptual measures may not perfectly align with actual behavioral performance. Future studies should incorporate direct behavioral measures—such as LMS log analyses of autonomous navigation decisions or observational checklists of technology use during microteaching sessions—to triangulate the self-report findings. Combining self-perceptual data with observed behavioral metrics would yield a more robust picture of the DICT model's effects on learner independence and technology integration, further strengthening the case for its adoption in teacher preparation curricula.

Conclusion

This paper has introduced, formalized, and empirically validated the DICT (Differentiated Integrated Computational Thinking) model, a novel instructional framework designed to simultaneously enhance creative thinking, learner independence, and technology integration competence among prospective elementary teachers. The core contribution of this work lies in its synthesis of differentiated instruction with computational thinking pedagogy within a digitally mediated environment, moving beyond the prevalent one-size-fits-all approaches in teacher education. By operationalizing learning profile mapping, dual-filter content selection, syntax-linked dynamic grouping, and a threshold-based adaptive facilitator reaction mechanism, the DICT model provides a formally defined, replicable structure that ensures each student—whether visual, auditory, or kinesthetic—engages with computational thinking operations in a manner aligned with their cognitive processing style.

The quasi-experimental results demonstrate statistically significant and practically meaningful improvements across all three target competencies. The experimental group achieved normalized gains nearly double those of the control group in creative thinking (0.45 vs. 0.23) and learner independence (0.38 vs. 0.14), with a large effect size for technology integration competence (Cohen's $d = 1.03$). The ablation analysis confirmed that the adaptive facilitator reaction mechanism, which systematically withholds intervention when engagement exceeds a predetermined threshold, contributes substantially to the development of learner autonomy. Furthermore, the model demonstrated equity-oriented outcomes, narrowing the performance gap for initially low-engagement students who exhibited creative thinking scores comparable to the broader experimental cohort.

The DICT model's principal contribution to the field is its formal integration of differentiation with computational thinking—two pedagogical domains that have historically operated in isolation. This synthesis addresses a critical gap in teacher preparation curricula, where prospective teachers often receive either personalized but cognitively shallow instruction or rigorous CT training that ignores individual variability. The model's five-phase syntactic structure provides a concrete blueprint that can be adapted to other disciplines and institutional contexts, contingent upon investment in appropriate digital infrastructure and faculty development. Future research should investigate the model's cross-disciplinary transferability, its longitudinal impact on teaching practices during field placements, and ethical safeguards to prevent modality-based stereotyping and algorithmic bias. For now, the DICT model stands as a validated, theoretically grounded framework for cultivating the 21st-century competencies essential for tomorrow's elementary educators.

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