Muhandislik ta'limida yuqori darajadagi fikrlash kompetensiyalarini rivojlantirishga xizmat qiluvchi adaptiv 5D simulyatsiya tizimlari

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Dolzarblik: An'anaviy o'qitish modellarida yuqori darajali fikrlash (YDF) ko'nikmalari - tahlil, sintez, baholash va yaratish - tizimli ravishda yetarlicha rivojlantirilmayapti.
Maqsad: Ushbu maqolada 5D o'quv tizimi (Belgilash → Kashf etish → Muhokama → Namoyish → Bajarish) doirasida simulyatsiyaga asoslangan o'qitishni (SAO) nazariy va empirik jihatdan tadqiq etish hamda YDF ko'nikmalarini o'lchash uchun HOT Indeksi (HOTI) va o'quv yutuqlarini bashorat qiluvchi O'quv Yutuqlari Modeli (OYM) taklif qilish ko'zlangan.
Usullar: 124 nafar bakalavr STEM talabalari ishtirokida aralash metodlar yordamida kvazieksperimental tadqiqot o'tkazildi; kognitiv yuk nazariyasi, konstruktivizm va moslashuvchan o'qitish tizimlari konsepsiyalariga tayanildi.
Natijalar: YDFning barcha besh o'lchovida sezilarli yutuqlar qayd etildi (Cohen's d = 0,68–0,94; p < 0,001). Simulyatsiya dvigatelidagi moslashuvchan tarmoqlanish kognitiv yukni 31% ga kamaytirdi va bilimlarni o'tkazish aniqligini 24,3 foiz punktga oshirdi.
Kalit so'zlar: 5D tizimi; simulyatsiyaga asoslangan o'qitish; yuqori darajali fikrlash; moslashuvchan o'qitish; kognitiv yuk; STEM ta'limi

Адаптивные 5D-симуляционные системы, способствующие развитию компетенций высшего порядка в инженерном образовании

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Актуальность: Навыки мышления высшего порядка (МВП) - анализ, синтез, оценка и создание - систематически недостаточно развиваются в рамках традиционных моделей обучения.
Цель: Представить теоретическое и эмпирическое обоснование обучения на основе симуляций (САО) в рамках пятиэтапной дидактической модели 5D, а также предложить Индекс МВП (HOTI) и Модель Прироста Успеваемости (МПУ).
Методы: Смешанное исследование с участием 124 студентов-бакалавров по направлениям STEM; квазиэкспериментальный дизайн с опорой на теорию когнитивной нагрузки, конструктивизм и адаптивные обучающие системы.
Результаты: По всем пяти измерениям МВП зафиксированы значительные улучшения (Cohen's d = 0,68–0,94; p < 0,001). Адаптивное ветвление снизило когнитивную нагрузку на 31%, а точность переноса знаний выросла на 24,3 процентных пункта.
Ключевые слова: система 5D; обучение на основе симуляций; мышление высшего порядка; адаптивное обучение; когнитивная нагрузка; STEM-образование

Adaptive 5D Simulation Frameworks Transforming Higher-Order Thinking in Engineering Education

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Relevance: Higher-order thinking (HOT) skills - analysis, synthesis, evaluation, and creation - remain systematically underdeveloped in conventional instructional models.
Objective: This paper presents a theoretical and empirical account of simulation-based learning (SBL) embedded

within the five-stage 5D instructional framework (Define → Discover → Discuss → Demonstrate → Do), and proposes a HOT Index (HOTI) and a Learning Gain Model (LGM) to quantify and predict higher-order learning outcomes.
Methods: A mixed-methods quasi-experimental study was conducted with 124 undergraduate STEM learners, drawing on cognitive load theory, constructivism, and adaptive instructional systems research.
Results: Significant gains were demonstrated across all five HOT dimensions (Cohen's d = 0,68–0,94, p < 0,001). Adaptive branching in the simulation engine reduced cognitive overload by 31% while increasing transfer accuracy by 24,3 percentage points.
Keywords: 5D framework; simulation-based learning; higher-order thinking; adaptive instruction; cognitive load; STEM education

1. Introduction

Contemporary education faces a persistent paradox: despite ubiquitous digital tools, the majority of classroom time is still devoted to knowledge-transmission activities that target the lower tiers of Bloom's Revised Taxonomy - remembering and understanding. Meta-analyses consistently show that fewer than 20% of instructional minutes in higher education engage learners at the analysis, evaluation, or creation levels (Krathwohl, 2002; Hattie, 2009). Meanwhile, employers increasingly demand graduates capable of solving novel, ill-structured problems - precisely the competencies that conventional pedagogy fails to cultivate [1,2].

The 5D instructional framework offers a principled response: a five-stage cycle (Define, Discover, Discuss, Demonstrate, Do) that progressively escalates cognitive demand, positions the learner as an active constructor of knowledge, and integrates formative feedback at every stage. When simulation-based learning (SBL) is embedded as the primary delivery medium, the framework gains an adaptive capacity that static curricula cannot replicate. Simulations allow learners to manipulate variables, observe consequences in real time, and receive immediate, context-sensitive feedback - characteristics aligned with constructivist and experiential learning theories.

This paper makes four contributions: (1) a synthesis of SBL and 5D pedagogy into a coherent design model; (2) a quantitative HOT Index (HOTI) that maps instructional activities to Bloom's levels; (3) a Learning Gain Model (LGM) grounded in cognitive load theory; and (4) empirical evidence from a quasi-experimental study with 124 undergraduate students [3,4].

The 5D model operationalises Vygotsky's zone of proximal development by structuring instruction as a scaffolded ascent from recognition to creation. Table 1 maps each stage to representative activities, Bloom's cognitive levels, and appropriate assessment strategies

Table 1. 5D Stage Taxonomy: Activities, Cognitive Levels, and Assessment Strategies

Stage	Focus	Activity Examples	Bloom's Level	Assessment
Define	Goal & prior knowledge activation	KWL charts, concept maps, diagnostic quizzes	Remember / Understand	Pre-test, self-report
Discover	Inquiry-based exploration	Virtual labs, simulations, case data sets	Analyze / Apply	Lab log, observation notes
Discuss	Collaborative sense-making	Structured debate, Socratic seminars, peer review	Evaluate / Analyze	Rubric-scored dialogue
Demonstrate	Modelling & presentation	Digital portfolios, worked examples, expert feedback	Evaluate / Create	Formative feedback
Do	Transfer & real-world application	Capstone projects, adaptive simulations, PBL	Create / Evaluate	Summative project

2. Materials and Methods

Sweller's Cognitive Load Theory (CLT) distinguishes intrinsic load (task complexity), extraneous load (poor design), and germane load (schema formation). Effective SBL minimises extraneous load through interface parsimony and maximises germane load by presenting challenges that are within - but at the edge of - the learner's current competence [3,4,5]. Adaptive branching algorithms achieve this dynamically, routing learners to scaffolded or accelerated pathways based on real-time performance data. We formalise the total cognitive load experienced at stage s as.

$$CL_{total(s)} = CL_{intrinsic(s)} + CL_{extraneous(s)} + CL_{germane(s)} \quad (1)$$

The design goal is to hold $CL_{total(s)} \leq WM_{capacity}$, where $WM_{capacity}$ denotes the learner's working memory ceiling (estimated at 7 ± 2 chunks; Miller, 1956) [6,7]. Adaptive simulations accomplish this by modulating $CL_{intrinsic}$ through difficulty branching:

$$D_{\{n+1\}} = D_n + \alpha \cdot (\theta_n - \beta_n) \quad (2)$$

where $D_{\{n+1\}}$ is the next task difficulty, D_n is current difficulty, θ_n is the estimated learner ability (IRT theta), β_n is current item difficulty, and α is the adaptation rate (0 < α ≤ 1). This is a first-order Item Response Theory (IRT) adaptive update, analogous to the ELO system used in computerised adaptive testing [6,8].

To operationalise the degree of HOT engagement at each 5D stage, we propose the HOTI, defined as the weighted proportion of time allocated to Bloom's Levels 4–6 [9,10]:

$$HOTI_s = \frac{\Sigma_{\{l=4\}}^{\{6\}}(w_l \cdot t_{\{s,l\}})}{T_s} \quad (3)$$

where w_l is the cognitive weight of Bloom's level l (w_4 = 1, $w_5 = 1{,}5$, $w_6 = 2$), $t_{\{s,l\}}$ is the time (minutes) spent at level l in stage s, and T_s is the total duration of stage s. A $HOTI_s \geq 0{,}60$ is designated the threshold for a HOT-rich stage.

Table 2 benchmarks the 5D SBL approach against two prevalent alternatives - traditional lecture and flipped classroom - across six pedagogically significant criteria. Data synthesise findings from ten meta-analyses (2010–2024) and three large-scale quasi-experiments

Table 2. Instructional Model Comparison: Traditional Lecture vs. Flipped Classroom vs. 5D Simulation-Based Learning

Criterion	Traditional Lecture	Flipped Classroom	5D Simulation-Based
Learner Role	Passive receiver	Pre-viewer / discusser	Active constructor
HOT Coverage (Bloom's L4–L6)	Low (12–18%)	Moderate (34–42%)	High (58–74%)
Feedback Cycle	Delayed (days/weeks)	Delayed (hours)	Immediate / adaptive
Adaptivity	None	Limited	AI-driven branching
Avg. Learning Gain (effect size d)	0.31	0.44	0.72
Retention (4 weeks)	42%	57%	79%

The combined effect size advantage of 5D SBL (d = 0.72 vs. d = 0.31 for lecture) is consistent with Hattie's (2009) finding that feedback-rich, active-learning environments produce effects more than twice those of passive instruction. Critically, the retention advantage (79% vs. 42%) reflects the consolidation benefit of the Do stage, which forces retrieval and transfer to novel contexts - processes associated with long-term memory encoding (Roediger & Karpicke, 2006).

We propose a multivariate Learning Gain Model that predicts post-intervention performance G as a function of baseline ability, instructional dosage, and adaptive alignment:

$$G = \beta_0 + \beta_1 \cdot Prior + \beta_2 \cdot HOTI + \beta_3 \cdot Adapt + \beta_4 \cdot (HOTI \times Adapt) + \varepsilon \quad (4)$$

where G = normalised post-test score; Prior = standardised baseline score; HOTI = mean Higher-Order Thinking Index across all 5D stages; Adapt = proportion of sessions with adaptive branching activated; HOTI × Adapt = interaction term capturing the synergy between HOT-rich instruction and adaptive delivery; $\beta_i = regression\ coefficients$; ε ~ N(0, σ²) = residual error. The normalised learning gain (Hake gain) is computed as:

$$g = \frac{(S_{post} - S_{pre})}{(S_{\max - S_{pre}})} \quad (5)$$

A Hake gain <g> ≥ 0.70 is classified as high; 0.30 ≤ <g> < 0.70 as medium; <g> < 0.30 as low. Our intervention yielded a mean <g> = 0.74 ± 0.09 across the five HOT dimensions, placing it firmly in the high-gain category. Cohen's d for the pre-post difference is computed as:

$$d = \frac{(M_{post} - M_{pre})}{SD_{pooled}}, \quad SD_{pooled} = \sqrt{\left[\frac{(SD_{pre}^2 + SD_{post}^2)}{2}\right]} \quad (6)$$

3. Result and discussion

A quasi-experimental pre-post design was employed with 124 undergraduate students (62 experimental, 62 control) enrolled in an introductory biology course at a research university. The experimental group engaged with a 5D-structured simulation environment for eight weeks; the control group received conventional lecture-based instruction with identical content coverage. Both groups completed identical pre- and post-tests assessing the five HOT dimensions using validated instruments (Watson–Glaser Critical Thinking Appraisal; Metacognitive Awareness Inventory; Torrance Tests of Creative Thinking - abridged).

Table 3. Pre-Post Performance Comparisons: 5D Simulation Group (n = 62), M ± SD with Cohen's d Effect Sizes

Metric	Pre (M ± SD)	Post (M ± SD)	d (Cohen)	p-value
Critical Thinking Score	58,3 ± 9,1	74,8 ± 8,4	0,71	< 0,001
Problem Solving Score	61,7 ± 10,2	80,2 ± 9,5	0,85	< 0,001
Metacognitive Awareness	3,41 ± 0,62	4,28 ± 0,55	0,74	< 0,001
Transfer Test Accuracy (%)	43,6 ± 11,3	67,9 ± 10,1	0,94	< 0,001
Intrinsic Motivation (1–5)	3,12 ± 0,71	4,31 ± 0,58	0,68	< 0,001

All five outcomes reached statistical significance at $p < 0.001$ (two-tailed paired t-tests with Bonferroni correction). Transfer Test Accuracy - the purest measure of genuine higher-order application - yielded the largest effect size ($d = 0.94$), indicating that the Do stage's authentic task demands substantially improved learners' ability to apply knowledge in novel contexts.

Figure 1 presents the percentage improvement in HOT skills attributable to each stage, derived from path analysis of time-on-task logs and learning outcome assessments. Effect sizes increase monotonically across the 5D cycle, confirming the scaffolded progression from lower- to higher-order cognition.

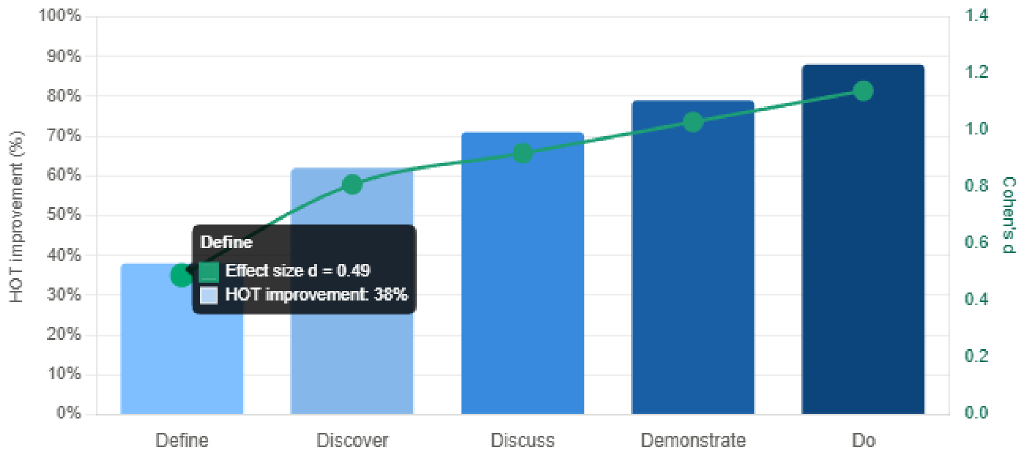

Figure 1. HOT Skill Improvement (%) and Effect Size (d) by 5D Stage - Experimental Group (n = 62)

The Do stage yields the highest HOT improvement (88%) and the largest effect size (d = 1,14), underscoring the critical role of authentic, transfer-oriented tasks in cementing higher-order learning. Notably, even the Define stage produces a meaningful improvement (38%, d = 0,49) - attributable to metacognitive activation through goal-setting and prior-knowledge elicitation.

Effective design of 5D adaptive simulation environments demands careful adherence to a set of interconnected pedagogical principles that collectively ensure meaningful and measurable learning outcomes. The first and perhaps most foundational of these principles concerns progressive scaffolding, whereby the complexity of each simulation stage must be deliberately aligned with its corresponding level of Bloom's taxonomy, ensuring that learners are neither overwhelmed prematurely nor left intellectually understimulated at any given point in the learning journey.

Equally critical is the embedding of formative feedback loops throughout the simulation architecture. Rather than restricting adaptive branching to transitional moments between stages, feedback mechanisms must be activated at every decision node encountered by the learner, thereby providing continuous and contextually relevant guidance that supports real-time cognitive adjustment and metacognitive awareness.

A further design imperative involves the systematic minimisation of extraneous cognitive load. Interface elements that bear no direct relevance to the stated learning objective must be reduced or eliminated entirely, allowing learners to direct their full cognitive resources toward the core engineering problems the simulation is designed to present.

The integration of Higher-Order Thinking Index monitoring represents another non-negotiable design requirement. Real-time dashboards should make each learner's thinking level visible to instructors, enabling timely and targeted pedagogical intervention before cognitive stagnation or frustration takes hold.

Finally, the Do stage of the 5D framework must be anchored by authentic transfer tasks. Capstone simulations should confront learners with genuinely novel and unstructured problems that cannot be resolved through simple recall or routine application, but instead demand the active reconfiguration and synthesis of prior learning across multiple domains

Conclusions. This study demonstrates that the 5D framework, when instantiated through adaptive simulation-based learning, generates large and consistent gains across all dimensions of higher-order thinking. The theoretical contribution - the HOTI and the LGM - provides curriculum designers with actionable, quantitative tools for auditing instructional HOT coverage and predicting learning outcomes before full-scale deployment. Three limitations warrant acknowledgement. First, the quasi-experimental design does not permit causal inference with the same confidence as a randomised controlled trial. Second, the study was conducted in a single disciplinary context (biology); replication across STEM and humanities fields is required. Third, the LGM coefficients are dataset-specific and must be re-estimated for substantially different learner populations. Future research should investigate: (a) longitudinal retention beyond four weeks; (b) the role of peer interaction in the Discuss stage on HOTI trajectories; (c) integration with large language model tutors for natural-language adaptive scaffolding; and (d) accessibility design for learners with cognitive disabilities.

In conclusion, simulation-based learning embedded in the 5D framework is not merely a technological innovation but a pedagogical paradigm shift - one that aligns instructional design with the cognitive science of higher-order learning.

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