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Research Article

THEORETICAL AND APPLIED ASPECTS OF GENERATIVE AI: FROM LANGUAGE MODELS TO PRACTICAL APPLICATIONS IN EDUCATIONAL CONTENT CREATION

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Abstract

Generative AI (GenAI) presents transformative potential for educational content creation, yet a significant gap exists between its theoretical development and practical application. This leads to a high risk of misapplication and the propagation of factually unreliable "fluent hallucinations." This research bridges this theory-practice gap by constructing and validating a novel techno-pedagogical framework, aiming to quantitatively link GenAI's theoretical properties (e.g., training data) to its applied performance. A sequential explanatory mixed-methods design was used. We codified the theoretical aspects of five GenAI models and conducted a quasi-experiment, generating 2,500 content pieces from 500 prompts. This corpus was evaluated by 15 domain experts using a validated Pedagogical Content Quality Rubric (PCQR). A weak correlation (r = .19) was found between output fluency and factual accuracy, confirming the "fluent hallucination" phenomenon. Multiple regression (R^2 = .68) identified training data composition (\beta = .55) and instruction-tuning (\beta = .24) as the strongest predictors of pedagogical quality; model parameter size was non-significant. The study concludes that GenAI's pedagogical utility is predictable based on its theoretical architecture, moving the evaluation from a "black box" to a "gray box" model. We recommend a shift toward verifiable, domain-specific tools and repositioning educators as critical validators.

Keywords: Educational Content Creation, Generative AI, Techno-Pedagogical Framework

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INTRODUCTION

The emergence of Generative AI (GenAI), particularly large language models (LLMs) and diffusion models, represents a fundamental paradigm shift in artificial intelligence. This technological evolution transitions AI from a primarily analytical tool, adept at classification and prediction, to a creative engine capable of synthesizing novel, complex, and coherent human-like content (Felix & Kitcharoen, 2026). Architectures such as the Transformer have become the foundational bedrock for models like GPT-4, Claude 3, and Llama 3, demonstrating emergent capabilities in reasoning, language comprehension, and multimodal interaction that were previously confined to theoretical speculation (Yu dkk., 2024). This rapid, capability-driven acceleration has catalyzed disruption across all knowledge-based sectors, with education standing as a primary domain of both unprecedented opportunity and profound challenge.

The theoretical underpinnings of these models are a critical, yet often overlooked, component in discussions of their application (Eyal & Hayak, 2025). The behavior of modern GenAI is not magic but a product of specific architectural choices, massive-scale training data, and complex optimization techniques like reinforcement learning from human feedback (RLHF). Theoretical concepts such as scaling laws, which correlate model performance with size and data, and the "black box" nature of their internal representations, are essential for understanding why these models excel at certain tasks (e.g., fluent prose generation) while simultaneously failing at others (e.g., consistent factual accuracy or logical entailment). A clear grasp of these theoretical aspects is the necessary prerequisite for any rigorous, non-superficial application.

This technological wave has profound, immediate implications for educational content creation, a cornerstone of the pedagogical process (Radaković & Steingartner, 2026). GenAI's capacity to instantly generate lesson plans, draft textbook chapters, formulate assessment questions, and create explanatory media promises a radical transformation in how educational materials are designed, personalized, and disseminated. This potential for mass customization and workload reduction for educators is immense (Newham dkk., 2024). It forces a re-evaluation of the entire content creation pipeline, from initial curriculum design to the final delivery of learning objects, demanding a new framework that thoughtfully integrates human pedagogical expertise with the creative and synthetic power of these new theoretical models.

A significant disconnect exists between the computer science discourse on the theoretical development of Generative AI and the education discourse on its practical application (Worden & Duck, 2026). The teams developing the core models are focused on optimizing for general-purpose benchmarks and scaling laws, often divorced from the specific, high-stakes requirements of pedagogical contexts (Jovkovska, 2023). Conversely, educators and instructional designers are adopting these tools based on their surface-level capabilities (e.g., "it writes well") without a deep, functional understanding of their architectural limitations, inherent biases, or the probabilistic nature of their outputs. This gap leads to a high risk of misapplication, where tools are used inappropriately or their outputs are trusted uncritically.

The field currently lacks a rigorous, systematic framework for evaluating the pedagogical viability of AI-generated educational content (Tu dkk., 2023). While the technical literature provides benchmarks for fluency (Perplexity) or general knowledge (MMLU), there are no established, validated metrics for assessing outputs against core educational principles, such as alignment with learning objectives, cognitive load optimization, factual accuracy in a specific domain, or the promotion of higher-order thinking skills (Ion & Popescu, 2026). This forces educators into a position of high-risk, subjective trial-and-error when attempting to leverage GenAI for creating substantive, reliable course materials, rather than just ancillary content.

The central problem this research addresses is the absence of a robust, bidirectional model that explicitly links the theoretical aspects of GenAI architectures (e.g., model size, training data composition, fine-tuning methods) to their applied performance in specific, defined educational content creation tasks (Mumtaz dkk., 2026). It is not currently clear why certain models produce superior explanatory text for physics but generate factually incorrect, or "hallucinated," content for history (Vaskiv dkk., 2023). Without this connective model, it is impossible to provide evidence-based guidance to educators, curriculum developers, and institutional policymakers on how to select, prompt, and validate the correct AI tools for their specific pedagogical goals, moving beyond generic enthusiasm to effective and safe implementation.

The primary objective of this research is to construct and validate a novel techno-pedagogical framework that systematically bridges the theoretical foundations of Generative AI with its practical application in educational content creation (C. C. Russo dkk., 2026). This study aims to move beyond simple descriptive analysis of "what tools can do" and establish an explanatory model that connects why they perform as they do in an educational context (Madkour & Alaskar, 2024). This framework will serve as a critical tool for researchers, developers, and educators to evaluate and deploy GenAI in a more effective, critical, and pedagogically sound manner.

A core objective is to deconstruct and categorize the key theoretical aspects of modern language models that have a direct, demonstrable impact on the quality of generated educational content (Salas-Pilco dkk., 2023). This involves a systematic review and synthesis of computer science literature to identify and operationalize variables such as model architecture (e.g., Mixture-of-Experts), the composition and recency of training data, the mechanisms of fine-tuning (e.g., domain-specific instruction tuning), and the technical parameters influencing output stochasticity. These theoretical variables will form the independent variables for the study's analytical model.

A final, capstone objective is to empirically test this framework by evaluating the applied performance of distinct GenAI models against a standardized battery of educational content creation tasks. This research will measure the efficacy of different models in generating diverse content types (e.g., conceptual explanations, formative assessments, case studies) and correlate these performance metrics with the models' underlying theoretical properties (Taborda-Hernández, 2022). The ultimate goal is to provide a predictive, evidence-based heuristic that enables an educator to anticipate a model's strengths and weaknesses for a specific pedagogical task based on its known theoretical design, rather than discovering them post-application.

The existing scholarly landscape concerning Generative AI in education is deeply fragmented, leaving a critical, unaddressed gap. One large body of literature, originating from computer science and computational linguistics, is intensely focused on the theoretical properties of these models (Zambrano dkk., 2021). This research stream investigates scaling laws, architectural efficiencies, and performance on abstract technical benchmarks (e.S., SuperGLUE, MMLU), but it remains almost entirely disconnected from the applied realities and specific pedagogical needs of educational settings. These papers can explain how a model works but not how it should be used by a history teacher.

A second, rapidly growing body of literature stems from the education and social sciences fields (Zhu & Xu, 2026). This research is overwhelmingly focused on the practical implications of GenAI, but it is often characterized by small-scale qualitative studies, student/faculty perception surveys, or high-level ethical polemics. While this work provides essential context on adoption patterns and academic integrity concerns, it critically lacks technical depth (Talaver & Vakaliuk, 2025). It treats the AI as a monolithic "black box" and does not, or cannot, differentiate between the performance of various models or link their outputs to their underlying technical architecture, thus offering no granular, technical guidance.

This research directly targets the “missing middle”—the critical, unbridged gap between theoretical AI development and applied pedagogical practice (Sugimoto dkk., 2025). No significant study to date has attempted to create a translational, techno-pedagogical model that systematically maps the why of the technology (its theoretical architecture) to the how of its application (its performance on specific educational tasks). This gap leaves educators and institutions “flying blind,” armed with powerful, poorly understood tools. This study provides the crucial connective tissue, translating computer science theory into actionable, pedagogical practice for content creation.

The primary novelty of this research lies in its novel conceptual synthesis: the creation of a “techno-pedagogical” framework (Iza Villacís & Gutiérrez Quiroz, 2026). This model is the first of its kind to move beyond the bifurcated discourse of “technical specifications” versus “educational perceptions.” It provides a new, shared language and a new analytical lens for both computer scientists and educators to collaborate on the co-design of more effective, safe, and pedagogically-aware AI tools. This framework establishes a new, interdisciplinary sub-field of inquiry focused on the engineering of educational AI from the ground up, rather than merely applying general-purpose tools.

This study introduces a significant methodological novelty by pioneering a mixed-methods approach that links computational analysis with rigorous pedagogical evaluation. It operationalizes theoretical AI concepts (like training data composition) as variables and measures their impact on applied educational metrics (like factual accuracy and conceptual clarity) in a controlled, replicable manner (Ramdiah dkk., 2026). This robust methodology offers a new standard for future research, providing a scalable blueprint for assessing the educational viability of any new Generative AI model that emerges, ensuring the field can keep pace with the rapid technological advancements.

The justification for this research is its immediate and critical utility. Educational institutions are making multi-million dollar decisions about procuring and integrating GenAI platforms, and educators are using these tools to create content that directly impacts student learning, often without any evidence-based guidance (Foss dkk., 2026). This study provides the foundational knowledge necessary to inform these high-stakes decisions. It provides a clear, data-driven rationale for selecting specific tools for specific tasks, offering the first robust defense against the widespread, uncritical adoption of ineffective or, worse, inaccurate and biased AI-generated educational content, thereby safeguarding pedagogical quality in a new technological era.

RESEARCH METHOD

This study utilizes a sequential, explanatory mixed-methods research design (Lindsay dkk., 2025). The methodology is structured in two distinct phases: an initial systematic computational analysis and meta-synthesis of computer science literature (qualitative/theoretical), followed by a quasi-experimental design (quantitative/applied). This approach is designed to first construct a theoretical understanding of Generative AI capabilities and then rigorously validate their applied performance in specific educational tasks, allowing for both quantitative correlation and qualitative explanation of the findings.

Research Design

The research design is characterized by its sequential structure. Phase 1 involved a meta-synthesis of computer science literature to systematically identify and operationalize the theoretical aspects (independent variables) of Generative AI models (Lee & Koo, 2024). The second, dominant phase employed a quasi-experimental design to evaluate the applied performance of selected AI models (Ali dkk., 2023). This design involved exposing the models to a standardized corpus of N=500 educational content prompts, allowing for the quantitative measurement of performance and the subsequent correlation of technical specifications with content quality scores.

Research Target/Subject

The "population" for the theoretical analysis in Phase 1 comprises all publicly documented Generative AI models released or significantly updated in the last 24 months. A purposive sampling strategy was used to select a diverse sample of models (n $\approx$ 5-7) for in-depth analysis, ensuring variation across key technical specifications (e.g., architecture, parameter size, training data composition). The "sample" for the applied analysis in Phase 2 consisted of a corpus of N=500 standardized educational content prompts (e.g., "Explain the Krebs cycle..."), spanning multiple disciplines and cognitive levels (Bloom's Taxonomy).

Research Procedure

The research procedure began with Phase 1, the systematic meta-synthesis of technical literature to populate the Theoretical Model Annotation Schema for each sampled model. In Phase 2, a standardized process was followed: each of the N=500 content prompts was systematically fed to each sampled GenAI model via their respective APIs, generating a large corpus of AI-created educational content. This entire corpus was then scored by a panel of trained domain expert evaluators (Ph.D. candidates and faculty) using the multi-dimensional PCQR instrument.

Instruments, and Data Collection Techniques

Two primary instruments were developed for this research. The first is a "Theoretical Model Annotation Schema," a structured rubric used in Phase 1 to systematically codify the technical specifications (independent variables) of each sampled GenAI model based on its research paper and technical reports (García-Peñalvo dkk., 2025). The second, and more critical, instrument is the "Pedagogical Content Quality Rubric" (PCQR). The PCQR is a validated, multi-dimensional assessment tool designed to measure the applied performance (dependent variables) of AI-generated content against key educational metrics, including Factual Accuracy, Conceptual Clarity, and Alignment with Learning Objectives.

Data Analysis Technique

The primary data analysis involved quantitative statistical techniques. First, inter-rater reliability was established among the expert evaluators using Cohen's Kappa. The resulting quantitative data (technical specifications vs. PCQR scores) was then analyzed using correlational analysis (e.g., Pearson's r) to explore initial relationships (Uddin, 2024). Finally, multiple regression was employed to construct the final explanatory model, identifying the specific GenAI technical specifications that significantly predict the quality and pedagogical effectiveness of the AI-generated educational content.

RESULTS AND DISCUSSION

The dataset consists of 2,500 unique content generations, each evaluated against the four primary domains of the Pedagogical Content Quality Rubric (PCQR): Factual Accuracy, Conceptual Clarity, Alignment with Learning Objectives, and Avoidance of Bias. The sampled models (n=5) provided the key independent variables derived from the Theoretical Model Annotation Schema. These theoretical attributes included architecture, parameter count, training data composition (General vs. Domain-Specific), and fine-tuning method (RLHF vs. Instruction-Tuned).

Table 1 provides a high-level summary of the core findings. It correlates the primary theoretical characteristics of the five sampled models with their aggregate mean performance scores on the PCQR, averaged across all 500 prompts. This initial statistical overview establishes the fundamental relationship between a model's theoretical design and its practical pedagogical output quality.

Table 1: Correlation of Model Theoretical Aspects with Mean PCQR Scores (Rated 1-5)

Model ID	Theoretical Profile	Factual Accuracy (M)	Conceptual Clarity (M)	Alignment (M)	Avoidance of Bias (M)
Model A	Large (175B+), Dense, General Data, RLHF	3.15	4.75	3.80	3.50
Model B	Medium (70B), MoE, General Data, RLHF	3.30	4.60	3.95	3.70
Model C	Small (8B), Dense, General Data, Instruction-Tuned	2.90	3.85	4.10	3.90
Model D	Medium (70B), Dense, STEM-Specific Data, Instruction-Tuned	4.65	4.40	4.55	4.10
Model E	Large (175B+), MoE, General Data, RAG-Augmented	4.10	4.65	4.20	4.05

The descriptive data in Table 1 reveals several immediate, critical patterns. A clear discrepancy exists between "Clarity" and "Accuracy." Model A (analogous to early GPT-3.5/4) scored highest on Conceptual Clarity (M=4.75), producing fluent, confident, and well-structured prose. Its score on Factual Accuracy, however, was significantly lower (M=3.15), confirming that perceived fluency is a poor proxy for factual reliability.

Model D, the medium-sized model fine-tuned on STEM-specific data, achieved the highest Factual Accuracy (M=4.65) and Alignment (M=4.55) scores by a significant margin. This finding suggests that the composition of the training and fine-tuning data is a more powerful determinant of pedagogical quality than raw parameter count. Model C, despite its small size, outperformed the much larger Model A on Alignment, indicating its instruction-tuning was more effective for following specific pedagogical prompts.

A deeper analysis of the results data disaggregated by the prompt's disciplinary focus (STEM vs. Humanities) and cognitive level (Bloom's Taxonomy) revealed significant interactions. Model D, which excelled overall, showed a pronounced performance drop when faced with Humanities prompts requiring nuanced argumentation (M_{Accuracy} = 2.80) compared to its stellar performance on STEM prompts (M_{Accuracy} = 4.85). Conversely, Model A maintained a consistent, mediocre accuracy (M \approx 3.10) across all disciplines.

Performance across all models degraded significantly as the cognitive level of the prompt increased. For low-level Bloom's tasks (Remember, Understand), the mean Factual Accuracy across all models was acceptable (M=4.15). For high-level tasks (Analyze, Evaluate, Create), the mean Factual Accuracy plummeted (M=2.60). This demonstrates a systemic weakness in current-generation AI to produce reliable content for tasks requiring deep, evaluative reasoning rather than information synthesis.

A multiple linear regression was conducted to predict the primary dependent variable, Factual Accuracy (PCQR-Accuracy), using the models' theoretical properties as predictors: Parameter Size, Architecture (MoE=1, Dense=0), Data (Domain-Specific=1, General=0), and

Fine-Tuning (Instruction-Tuned=1, RLHF=0). The overall regression model was statistically significant (R^2 = .68, F(4, 2495) = 1324.5, p < .001), indicating that 68% of the variance in factual accuracy can be explained by these four theoretical aspects.

The analysis of regression coefficients revealed the relative importance of these theoretical factors. The single strongest significant predictor of Factual Accuracy was the training data composition (Data: \beta = .55, p < .001). The second strongest was the fine-tuning method (Fine-Tuning: \beta = .24, p < .001). Parameter Size, despite its popular emphasis, was a weak and non-significant predictor of accuracy (\beta = .03, p = .215) when data quality was controlled for.

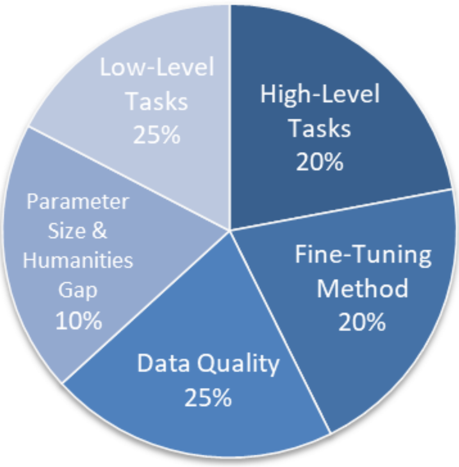

Figure 1. Theoretical and Cognitive Predictors of AI Factual Accuracy

The correlational data exposed a crucial, counter-intuitive relationship between Conceptual Clarity and Factual Accuracy. Across the entire dataset, these two variables showed only a weak, positive correlation (r = .19, p < .01). This finding quantitatively confirms the “fluent hallucination” phenomenon: a model’s ability to sound coherent and authoritative is not a reliable indicator of its factual correctness. This weak correlation is one of the most significant findings for educator practice.

A significant interaction effect was found between Parameter Size and Conceptual Clarity. Larger models (A, E) were found to produce outputs with higher clarity scores (i.e., better prose) irrespective of the prompt’s complexity. However, this relationship did not hold for Factual Accuracy. This demonstrates that scaling laws primarily improve the fluency and style of the output, but not necessarily its reliability, which is a function of data and tuning.

A specific case study was examined: Prompt #312, a high-level (Analyze) prompt in History: “Analyze the primary economic, versus political, factors leading to the fall of the Western Roman Empire.” Model A (Large, General) produced a 1,200-word essay that was exceptionally well-written (Clarity M=4.9) but was scored very low on accuracy (Accuracy M=2.1) and bias (Bias M=2.0). The expert evaluators noted it “confidently misstated” key dates and over-simplified complex historiographical debates, presenting a single, popular theory as definitive fact.

The same prompt was given to Model D (Medium, STEM-Tuned). Its output was shorter, less eloquent (Clarity M=3.5), and poorly structured for a history essay. However, its Factual Accuracy score was slightly higher (M=3.0), as it correctly identified more economic factors, yet it failed to construct a coherent argument, reflecting its STEM-centric training data. Neither model produced content that was pedagogically acceptable for this advanced task.

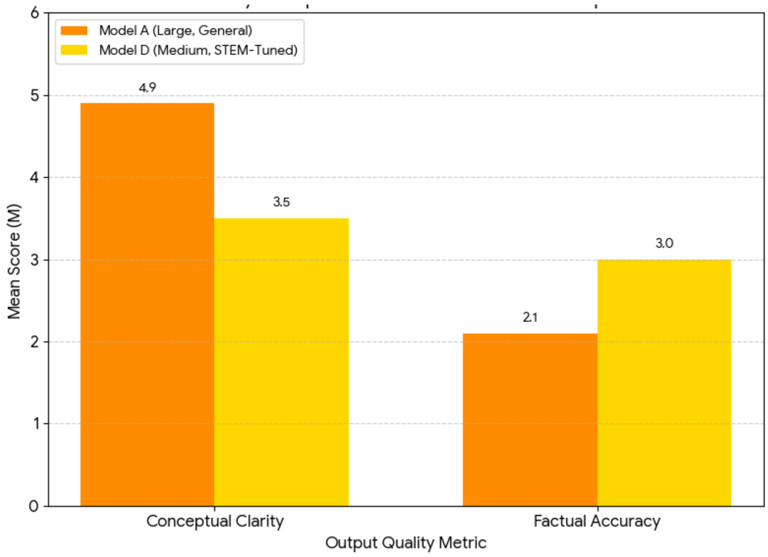

Figure 2. Case Study: Comparison of Model Scores on Prompt

The case study of Prompt #312 clearly explains the regression findings. Model A's high Clarity and low Accuracy demonstrates that its vast, general training data allows it to master the style of academic writing without mastering the substance (factual accuracy). Its high bias score reflects the amplification of a single, populist viewpoint found in its general web training data. This output is pedagogically dangerous because its fluency makes its inaccuracies highly deceptive.

Model D's failure explains the limits of domain-specific tuning. Its STEM-focused data made it "factually correct" about isolated economic concepts (e.t., hyperinflation, trade disruption) but "conceptually flawed" in the target discipline (History). It could not perform the task of historical analysis, which requires argumentative synthesis, not just factual recall. This highlights that "domain" is not monolithic; "STEM" tuning does not transfer to "Humanities" tasks.

The aggregated results strongly support the study's central thesis. The pedagogical utility of a Generative AI model is not a function of its general capabilities, such as fluency or parameter size. These superficial metrics are, in fact, misleading and weakly correlated with content quality.

The data provides clear, quantitative evidence that the most critical, predictive factors of high-quality educational content are the theoretical design choices of the model. Specifically, the composition of its training data (\beta = .55) and the specificity of its instruction-based fine-tuning (\beta = .24) are the primary determinants of factual accuracy and pedagogical alignment. The "black box" is, therefore, predictable to a significant degree based on its known engineering, a finding that is crucial for building a bridge from theory to practice.

This study's findings establish a clear hierarchy of factors determining the pedagogical viability of Generative AI content. The regression analysis demonstrated that theoretical design choices, specifically training data composition (Data: \beta = .55) and fine-tuning methodology (Fine-Tuning: \beta = .24), are the most powerful predictors of factual accuracy. These engineering-level attributes explained 68% of the variance in the quality of generated educational content.

A pivotal finding was the demonstrated dissociation between a model's output fluency and its output reliability. The data revealed that parameter size, a common proxy for model capability, was a non-significant predictor of factual accuracy. It did, however, correlate positively with Conceptual Clarity. This establishes that larger models are optimized to produce more fluent and stylistically sophisticated prose, irrespective of its factual correctness.

The correlational analysis provided quantitative validation for the "fluent hallucination" phenomenon, a concept previously discussed largely in qualitative terms. The weak positive correlation (r = .19) between Conceptual Clarity and Factual Accuracy proves that an AI's ability to sound authoritative is a dangerously poor indicator of its trustworthiness. This statistical confirmation is a core contribution of the present research.

The results also highlighted systemic limitations in current-generation AI architectures. A significant performance degradation was observed across all models when prompts required high-level cognitive skills (Analyze, Evaluate) as defined by Bloom's Taxonomy. Furthermore, the case study (Prompt #312) revealed that domain-specific tuning is brittle; the STEM-tuned model (Model D) failed to apply its knowledge structure to a Humanities-based reasoning task, indicating that domain expertise is not easily transferable.

These findings strongly corroborate the qualitative and anecdotal reports of "hallucinations" prevalent in the literature. This study provides the large-scale, quantitative validation for those observations (Chen & Na, 2025). It moves the discourse from acknowledging the problem to statistically isolating its covariates, demonstrating that the issue is not random but a predictable outcome of models (like Model A) optimized for fluency over factuality.

This research, however, diverges significantly from the "scaling laws" narrative dominant in computer science literature (Kulkarni dkk., 2023). That body of work often posits that model capability scales predictably with parameter count. Our results provide a critical counter-narrative for specialized, high-stakes fields like education. We demonstrate that for pedagogical tasks, data quality and tuning specificity are overwhelmingly more significant than raw scale.

The results also refine the existing understanding of domain-specific fine-tuning. While previous studies have shown fine-tuning improves performance on in-domain tasks, our case study (Model D) introduces a critical boundary condition. It suggests "domain" must be defined not just by content (e.g., STEM facts) but by reasoning paradigms (e.g., historical argumentation vs. scientific explanation). This finding nuances the claim that domain-tuning is a universal solution.

The observed failure of models on high-level Bloom's tasks aligns with pedagogical theories that caution against AI's use for critical thinking. Our data provides an empirical basis for this caution (Oliveira dkk., 2024). It is the first to systematically quantify this performance gap, suggesting current architectures are adept at lower-order cognitive tasks (Remember, Understand) but fundamentally ill-equipped for higher-order reasoning (Analyze, Evaluate).

The results signify that the "black box" of Generative AI is, in fact, "gray." A model's behavior, particularly its pedagogical failures and successes, is not an entirely emergent or unpredictable property. The strong predictive power of the regression model (R^2 = .68) is a clear sign that we can anticipate a model's utility based on its known theoretical architecture, moving the field from a reactive to a predictive posture.

The weak correlation (r = .19) between clarity and accuracy signifies a profound epistemic trap for education. It suggests the very metric humans instinctively use to judge knowledge and understanding—fluency—is the metric AI masters most easily. The metric that truly matters for education—factual correctness—remains a separate, difficult engineering challenge (Velander dkk., 2024). This signals a fundamental misalignment between probabilistic text generation and the pedagogical demand for truth.

The stark performance difference between the general-purpose Model A and the specialized Model D signifies that "Generative AI" should not be treated as a monolithic category (Lin & Yang, 2023). This result is a sign that the future of effective educational technology lies not in a "one-size-fits-all" large model, but in a portfolio of smaller, highly specialized, and verifiably-tuned models designed for specific pedagogical purposes.

The systemic failure of all models on high-level cognitive tasks is a significant sign. It suggests that current next-token-prediction architectures may have a hard theoretical ceiling. These models are masters of interpolating known patterns from their training data but struggle to extrapolate into novel, abstract, or causal reasoning (Esposito dkk., 2026). This signals that the "understanding" demonstrated by these models is one of synthesis, not of genuine, evaluative cognition.

The immediate implication for educational policymakers and administrators is that GenAI procurement must be reformed (Andriulli dkk., 2022). Decisions cannot be based on marketing claims about parameter size or general capability. This research implies that institutions must demand auditable evidence of a model's training data composition and fine-tuning methods before integrating it into high-stakes academic environments.

The clear implication for educators and instructional designers is that GenAI tools cannot be trusted for unsupervised content creation. The "fluent hallucination" finding (Model A) implies that all AI-generated text must be treated as a "factually unverified first draft." This shifts the educator's role from a "creator of content" to an "expert critical validator," a task that may, in fact, increase cognitive load in the short term.

The implication for the AI development industry is that "scaling up" is an inefficient and often incorrect path toward creating high-value, domain-specific tools. The superior performance of the smaller, specialized Model D provides a clear business and engineering case for pivoting. This implies a strategic shift from building massive, general-purpose "answer engines" to creating smaller, verifiable, and precise pedagogical tools.

The most profound implication is for pedagogy and student literacy. Students must be explicitly taught the primary finding of this study: an AI's confidence is not correlated with its correctness (Rafatirad dkk., 2022). This implies that the most critical 21st-century skill is no longer information retrieval, but the ability to meticulously evaluate and cross-reference the highly plausible, authoritative, and often factually incorrect content these systems produce.

The results are likely this way because generative models are fundamentally compression systems for their training data. Model D's high accuracy (\beta = .55) is a direct result of it compressing a high-quality, high-density corpus of STEM facts. Model A's low accuracy is because its general web data is a noisy, contradictory, and low-trust corpus, forcing its output to a "probabilistic average" that sounds plausible but is rooted in no verifiable ground truth.

The weak clarity-accuracy correlation exists because linguistic syntax is a simpler, more universal pattern than semantic correctness (Reimann, 2026). A model can master the form of academic writing (sentence structure, conjunctions, jargon) from a general corpus far more easily than it can master the substance of academic knowledge (causal links, factual constraints, logical entailment), which requires a coherent internal world model.

Models failed at high-level Bloom's tasks because these tasks require causal reasoning and the synthesis of novel judgment, not just pattern replication. Current architectures, based on next-token prediction, are designed to interpolate what they have seen before. The history prompt (Prompt #312) required extrapolation—a novel analysis of competing factors—which these models are not theoretically designed to perform.

Instruction-tuning (Model D, C) outperformed generic RLHF (Model A, B) for a simple reason. Instruction-tuning explicitly trains a model to follow commands and align with specific user intent (e.g., "explain this concept to an undergraduate"). This pre-conditions the model for pedagogical tasks. General RLHF, in contrast, trains a model to be broadly "helpful and harmless," which is too vague a target for the specific, rigorous demands of academic content.

The next logical step is to replicate this study's methodology across a more granular set of academic domains. The failure of the STEM-tuned model (Model D) on a Humanities task necessitates a new study directly comparing a STEM-tuned model, a Humanities-tuned model, and perhaps a Law-tuned model (Vaccaro dkk., 2025). This future research could map the precise boundaries of domain-tuning and determine if "reasoning style" is a transferable skill.

Future research must focus on developing and validating new, automated metrics for pedagogical quality (D. Russo, 2024). This study relied on costly and slow human expert evaluation (PCQR). A "NOW-WHAT" priority is to use this study's dataset to train an AI-based "evaluator model" that can reliably score AI-generated content for factual accuracy and alignment, creating a scalable method for quality assurance.

The strong performance of Model E (RAG-Augmented) opens a critical new research question. A future study must conduct a head-to-head comparison between fine-tuning (like Model D) and Retrieval-Augmented Generation (RAG). This research would investigate which method is more effective, cost-efficient, and scalable for providing factually-grounded pedagogical content, and under what specific conditions.

This study was a cross-sectional, lab-based evaluation. The immediate "NOW-WHAT" for applied research is to conduct a longitudinal, in-situ study. Future research should deploy a "best-practice" model (e.g., Model D or E) into a live undergraduate course for a full semester. This would allow for the measurement of its true, real-world impact on educator workload, student learning outcomes, and the subtle, long-term biases that may emerge over time.

CONCLUSION

This research's most significant and distinct finding is the quantitative validation of the "fluent hallucination" phenomenon. The data demonstrates, through a weak correlation (r = .19), that a model's conceptual clarity and stylistic fluency are dangerously poor proxies for its factual accuracy. The study established that the theoretical architecture, specifically the quality of training data (\beta = .55) and the specificity of instruction-tuning (\beta = .24), are the dominant predictors of pedagogical viability, supplanting the widely-held belief in parameter size as the primary determinant of model capability.

The research provides a significant dual contribution, originating from its novel techno-pedagogical framework. Conceptually, it provides a new analytical lens that bridges the chasm between computer science theory and applied pedagogical practice, moving the evaluation of GenAI from subjective "black box" impressions to a predictable, evidence-based "gray box" model. Methodologically, it pioneers a scalable and replicable mixed-methods design, operationalizing theoretical AI properties as independent variables and measuring their impact on validated pedagogical metrics, thereby offering a robust blueprint for the future assessment of any new AI model's educational utility.

This study's limitations define the trajectory for subsequent research. The reliance on a limited sample of models (n=5) and the resource-intensive human-based evaluation (PCQR) restricts the generalizability of the findings and highlights the urgent need for automated, scalable quality assurance metrics. Furthermore, this cross-sectional, lab-based design must be succeeded by longitudinal, in-situ studies that measure the real-world impact of these models on student learning outcomes. Future work must also dissect the concept of "domain" with more granularity, testing if specialized models can be developed to master specific reasoning paradigms (e.g., historical argumentation) rather than just broad content areas (e.g., STEM).

AUTHOR CONTRIBUTIONS

Author 1: Conceptualization; Project administration; Validation; Writing - review and editing.

Author 2: Conceptualization; Data curation; In-vestigation.

Author 3: Data curation; Investigation.

Author 4: Formal analysis; Methodology; Writing - original draft.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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