Aligning Faculty Dynamic Capabilities and Institutional Legitimacy in AI-Enabled Business Analytics Pedagogy: A Conceptual Framework and Research Agenda

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Abstract

We derive three propositions and outline a focused mixed-methods research agenda that operationalizes institutional pressures, faculty capabilities, and strategic choice, while foregrounding ethics, consent, and integrity guardrails. The article shifts AI-enabled business analytics education beyond descriptive adoption accounts toward theory-driven explanation of when and why learning value is created.

Keywords: generative AI; large language models; business analytics education; institutional legitimacy; dynamic capabilities

Introduction

This manuscript develops a conceptual, theory-building framework with propositions and an operationalization-oriented research agenda; it does not report empirical findings. Technological innovation disrupts established practices across organizations and educational institutions, reshaping norms of competence, assessment, and professional preparation. In higher education, innovations that alter assessment and curriculum can raise legitimacy concerns—whether stakeholders perceive practices as appropriate, rigorous, and trustworthy. In business analytics (BA) education, LLMs intensify this concern because they can complete tasks previously treated as visible evidence of learning (e.g., writing and debugging code unaided). The practical question is therefore instructional and governance-oriented: how should BA programs teach and assess in the AI era so graduates become AI-ready while credibility, comparability, and assessment integrity are maintained?

We define institutional legitimacy as stakeholders' shared expectations about proper organizational behavior and credible markers of rigor (e.g., transparency of assessment standards, integrity safeguards, and alignment with disciplinary norms). In many settings, legitimacy and AI-readiness are not opposites; employers, accreditors, and students often want both. Tension emerges when legacy markers of rigor (such as syntax recall as a proxy for competence) collide with AI-enabled automation and when institutions respond through visible AI adoption that is weakly coupled to redesigned learning outcomes.

We contend that current discussions of LLM adoption in business analytics education remain largely descriptive—focused on tool usage—rather than explanatory, offering limited insight into why adoption produces divergent learning outcomes across institutional contexts.

Without deliberate governance and pedagogical redesign, AI integration can institutionalize superficial compliance: students may meet formal assignment requirements while bypassing analytical reasoning. Conversely, when faculty redesign instruction and assessment to foreground interpretive judgment, AI can become a lever for higher-order learning.

To explain these divergent outcomes, we integrate three organizational lenses. Institutional Theory clarifies how external pressures can encourage symbolic adoption and decoupling. The Resource-Based View foregrounds faculty expertise as a strategic resource that can differentiate learning value. Dynamic Capabilities specify how faculty sense, seize, and transform instructional and assessment practices in response to disruption. Building on this integrated logic, we ask: (1) Under what conditions does LLM adoption in BA education become ceremonial rather than substantive? (2) How do faculty dynamic capabilities shape whether instruction shifts from code efficacy to insight efficacy? (3) How does strategic choice mediate alignment between legitimacy requirements and pedagogical innovation?

We contribute (a) clear construct definitions (legitimacy, ceremonial adoption/decoupling, code efficacy vs. insight efficacy), (b) three propositions linking institutional pressures, faculty capabilities, and organizational capital, and (c) a focused research agenda that is explicitly framed as future work (not a completed empirical study), including ethics and consent considerations for AI-enabled classroom research.

Theoretical Framework

Institutional Theory: Pressures, Isomorphism, and Legitimacy

In this paper, legitimacy refers to stakeholders' shared expectations that educational practices are appropriate, credible, and consistent with accepted markers of rigor (e.g., assessment integrity, transparency, and comparability). Legitimacy pressures can originate from accreditation standards, employer expectations, peer institution practices, and internal governance norms.

Decoupling describes a weak coupling between formal structures (e.g., policies stating AI is integrated) and the actual learning processes and assessment designs that would substantively develop targeted competencies. Ceremonial adoption refers to symbolic incorporation of AI tools that signals modernity without corresponding redesign of objectives, learning activities, and evaluation.

Institutional Theory (IT) provides a foundational lens for understanding how organizations respond to environmental pressures by adopting formal structures that signal legitimacy. Scott and Davis (2000) define rational systems as organizations oriented toward specific goals and characterized by highly formalized social structures. Building on this view, Meyer and Rowan (1977) argue that organizations are not purely rational actors; instead, they are embedded in broader normative, social, and cultural environments that shape behavior beyond technical efficiency. These environments give rise to rationalized myths—widely accepted practices that organizations adopt not because they are demonstrably effective, but because they are socially constructed as appropriate or necessary for organizational survival.

The adoption of rationalized myths generates isomorphic pressures within organizational fields, increasing the likelihood that organizations will converge on similar structures and practices (DiMaggio & Powell, 1983). An unintended consequence of this adoption is decoupling; whereby formal structures signal compliance and legitimacy while internal practices remain weakly aligned with actual operational outcomes. Within this framework, the institutional environment constitutes an ecology composed of regulators, peer organizations, professional norms, and cultural expectations that collectively establish the "rules of the game" governing organizational action (Thornton & Ocasio, 1999).

In higher education, legitimacy is pursued through signals of rigor (e.g., accreditation alignment, curricular coverage, transparent standards) and through visible adoption of practices that communicate relevance. When AI becomes such a signal, institutions may adopt policies and public narratives that imply pedagogical modernization even when assessment design, attribution norms, and learning objectives remain unchanged.

In the current technological landscape, institutional narratives about AI can function like rationalized myths—widely endorsed signals of modernity that may outpace evidence about pedagogical effectiveness—thereby increasing the risk of symbolic adoption when governance and assessment redesign lag behind.

When these practices spread widely, the result is mimetic isomorphism, driven by conformity to seem legitimate rather than pedagogical differentiation for value. While such responses can enhance perceptions of relevance, it also heightens the risk of decoupling. Institutions may adopt the visible form of AI-enabled instruction while leaving underlying pedagogical practices largely unchanged – classic decoupling.

Higher education institutions, as highly formalized organizations, frequently exhibit this pattern of symbolic adoption. In the context of AI, institutions may mandate the use of generative tools primarily to signal innovation and responsiveness. However, classroom implementation often remains superficial, inconsistently structured, or poorly aligned with learning objectives. In such cases, AI functions as a symbolic implementation rather than a value-add instructional resource. This form of decoupling helps explain organizational behavior in which formal adoption contradicts educational effectiveness: programs appear to teach the future of analytics through visible AI integration, while students primarily use these tools to bypass learning processes rather than deepen analytical understanding.

Illustrative classroom-level manifestations of decoupling (conceptual examples)

• Example 1 (policy–practice gap): The syllabus states "AI is integrated," yet assignments and rubrics remain unchanged; students can submit polished code/output generated by an LLM with minimal requirement to justify assumptions, diagnose errors, or interpret model behavior.

• Example 2 (integrity gap): A program encourages AI use but does not specify permitted/prohibited uses or attribution norms; students infer "anything goes," and submissions increasingly signal completion rather than demonstrated reasoning.

• Example 3 (comparability gap): Sections adopt inconsistent AI rules (one bans AI, another requires it), producing uneven competence signals and stakeholder doubts about fairness, comparability, and rigor.

These examples are not empirical claims; they are conceptual illustrations of the policy–practice distance that Institutional Theory calls decoupling.

Resource-Based View: Faculty as Strategic Assets

The Resource-Based View (RBV) offers a complementary perspective for understanding how organizations generate sustained value through the development and deployment of internal resources. Foundational work by Penrose (1959) and Barney (1991, 2001) conceptualizes organizations as heterogeneous bundles of resources whose strategic value depends on how effectively they are utilized. Within this framework, the unit of analysis shifts to the microlevel of the organization itself, emphasizing internal differentiation rather than environmental conformity. Barney (1991) distinguishes among physical, human, and organizational capital, arguing that resources confer sustained advantage when they are Valuable, Rare, Inimitable, and Non-Substitutable (VRIN).

Higher education institutions derive much of their value from concentrated knowledge and expertise. As technical analytics skills become more standardized—and increasingly supported by AI—faculty expertise shifts from delivering syntax to architecting learning: designing tasks, rubrics, and integrity protocols that cultivate interpretive judgment. In this sense, faculty operate as entrepreneurial learning facilitators whose instructional design choices can differentiate programs and graduate capabilities.

While the RBV emphasizes the strategic importance of resource heterogeneity, its explanatory power is enhanced by integrating the concept of dynamic capabilities. Teece, Pisano, and Shuen (1997) argue that in uncertain environments, static resources alone are insufficient. Organizations must also possess the capacity to sense, seize, and transform resources in response to change. In the context of AI-enabled pedagogy, dynamic capabilities provide a mechanism for understanding how faculty respond to the disruptive entry of Large Language Models (LLMs) into curricula and assessment practices.

Despite the theoretical promise of dynamic capabilities, their value is often recognized only retrospectively within higher education institutions (Barney, 1991). Faculty innovation is constrained by accreditation requirements, standardized curricula, and assessment norms that prioritize stability and comparability. Due to these limitations, even when faculty possess the capabilities, the room to experiment is low. As a result, educators face a strategic risk: exercising dynamic capabilities too visibly may threaten perceived legitimacy, while failing to innovate risks rendering instructional practices obsolete.

Faculty dynamic capabilities in AI-enabled pedagogy can be described as sensing, seizing, and transforming. Sensing is the ability to distinguish AI uses that create learning value from those adopted mainly as symbolic compliance. Seizing is the capacity to redesign activities and assessments to capture pedagogical value while navigating legitimacy constraints (e.g., comparability and integrity). Transforming is the sustained reconfiguration of curricula and assessment so that AI automates lower-order tasks while instruction and evaluation foreground insight efficacy.

Secondly, seizing involves utilizing available resources to capture pedagogical value from AI technologies despite institutional constraints. In practice, this requires navigating the tension between standardized assessment practices that support legitimacy and the need to redesign learning activities that use generative AI productively. Seizing therefore represents an act of strategic choice, in which faculty negotiate the boundary between external conformity (institutional pressures) and internal differentiation (RBV) (Child, 1972).

Finally, transforming entails the ongoing reconfiguration of curricula and assessment to prevent the hollowing out of internal knowledge. For instance, as AI can automate lower-order cognitive tasks, faculty must redesign learning environments to assess critical reasoning and what this paper conceptualizes as insight efficacy. This transformation is a continuous process of building and reconfiguring to ensure that the human capital developed through education remains difficult to substitute and pedagogically meaningful – in order to sustain forms of competitive advantage that remain difficult to imitate.

If this active transformation does not take place, AI adoption can be perceived as largely ceremonial. Courses may appear technologically advanced through visible AI integration, however, realized learning outcomes remain static or regress, reinforcing the decoupling.

Dynamic Alignment Model of AI Pedagogy

Institutional Theory and the Resource-Based View are frequently positioned as competing explanations of organizational survival, yet their divergence reflects differences in analytical focus rather than theoretical incompatibility. Critics of Institutional Theory argue that it underemphasizes agency and internal differentiation, while critics of the Resource-Based View note its limited attention to the social and institutional contexts that shape which resources are valued and how they are deployed. When examined together, these perspectives operate at distinct but complementary levels of analysis. Institutional Theory emphasizes macro-level processes—fields, norms, and legitimacy pressures—while the Resource-Based View focuses on micro-level processes related to internal resources and capabilities.

From an Institutional Theory perspective, survival of an organization is associated with isomorphism: organizations increase their likelihood of persistence by conforming to dominant practices and structures within their field. In contrast, the Resource-Based View conceptualizes survival through heterogeneity, arguing that organizations derive sustained advantage from resources that are difficult to imitate or substitute. This contrast creates a persistent tension. Efforts to differentiate through novel resources or practices may enhance internal value creation but risk undermining external legitimacy, producing what has been described as a classic organizational double-bind.

Recent scholarship suggests that this tension need not be resolved by privileging one perspective over the other. Oliver (1997) argues that organizations can exercise strategic responses to institutional pressures, while Patnaik et al. (2022) demonstrate that integrating Institutional Theory and RBV yields a more comprehensive understanding of organizational growth. Building on this combined logic, we propose the Dynamic Alignment Model of AI Pedagogy to explain how educational organizations actively bridge distant, macro-level institutional forces and proximate, micro-level resource configurations. In this model, faculty dynamic capabilities function as the connective tissue linking external expectations to internal capability development, showing that the theories are conjoined rather than juxtaposed.

Higher education institutions are particularly well suited to this dual perspective. As producers of knowledge, universities operate under strong institutional constraints while also competing for legitimacy. At the macro level, institutional processes govern the overall compliance with external bodies. At the micro level, pedagogical practice unfolds through individual faculty decisions such as the integration of technical resources (example: LLMs).

This dual pressure creates a challenge for innovation in AI-enabled pedagogy. The benefits of RBV-driven initiatives—such as redesigned curricula—often materialize only after implementation. During this interim period, institutions may face legitimacy risks if new pedagogical approaches deviate from established "rationalized myths" of rigor and standardization. Once successful outcomes become visible, peer institutions may mimic the innovation, adopting its formal features while neglecting the underlying pedagogical logic. Such mimicry erodes the rarity and inimitability of the original resource and can intensify decoupling as form is reproduced without substance.

The Dynamic Alignment Model of AI Pedagogy provides a practical lens for navigating this double bind in educational contexts. For faculty, the tension becomes concrete when pedagogical innovation threatens established markers of academic robustness. A radically AI-enabled curriculum may enhance students' analytical differentiation but risk resistance from accrediting bodies that prioritize traditional demonstrations of technical proficiency. Conversely, strict adherence to legacy instructional practices preserves legitimacy while failing to prepare students for environments shaped by automation and AI.

By adopting a Dynamic Alignment Model perspective, educators could exercise agency over micro-level instructional design, strategically reshaping learning activities to leverage AI in ways that deepen inquiry rather than bypass it. In doing so, institutions reduce the risk of decoupling and move toward a more integrated alignment between external legitimacy and internal educational differentiation.

The Context of AI in Business Education

From Code to Insight: The Shift in Pedagogical Value

This framework does not advocate eliminating coding from business analytics curricula; it calls for recalibrating what is taught and assessed. Foundational syntax and debugging remain necessary for students to read, validate, and modify code, but assessment should increasingly target interpretive judgment (model critique, assumption checking, error analysis, decision justification, and responsible deployment). In AI-enabled contexts, rigor shifts from producing code unaided to demonstrating transparent reasoning about code- and model-generated outputs under explicit integrity constraints.

Implications for Teaching and Assessing Coding in the AI Era

This framework retains coding as a core competency, but it distinguishes between (a) coding-as-production and (b) coding-as-literacy. Coding-as-production (writing from scratch) can be assessed selectively in constrained conditions (e.g., timed in-class work, partial-tool access, or scaffolded prompts) to verify baseline competence. Coding-as-literacy (reading, validating, modifying, and stress-testing code) should become the dominant emphasis, because it matches professional practice and supports responsible AI use.

Accordingly, assessment can shift toward tasks that require students to: (1) audit AI-generated code for correctness, security, and data leakage; (2) explain model assumptions and limitations; (3) conduct error analysis and robustness checks; and (4) justify decisions using domain context and stakeholder constraints. These moves preserve rigor and comparability while making AI use visible, governed, and learning-aligned.

Existing research reports mixed findings on whether LLMs reliably sustain higher-order engagement in educational settings. Even when LLMs can support analysis and evaluation, these opportunities unfold within institutional environments structured around standardized curricula, accreditation expectations, and assessment models designed for relatively stable forms of instruction.

This misalignment exposes a point of contention in AI-enabled Business Analytics education: prioritizing insight efficacy. When faculty adoption of LLMs is driven primarily by pressures to signal technological relevance rather than by pedagogical intent, institutions face a higher risk of decoupling. In such cases, the formal inclusion of AI tools serves as a marker of legitimacy, while underlying instructional practices remain weakly aligned with learning objectives (DiMaggio & Powell, 1983).

Under decoupling, AI integration can enhance the appearance of efficiency or innovation without improving—and sometimes undermining—learning outcomes. In such settings, AI may be visibly embedded in coursework while contributing little to higher-order reasoning because objectives, rubrics, and integrity guardrails were not redesigned. Without intentional instructional redesign, LLMs risk reinforcing superficial task completion rather than developing the interpretive capabilities central to insight efficacy.

Metamimesis: Homogeneity in the Age of Algorithmic Output

Adoption of large language models in higher education can be shaped by mimetic isomorphism, as institutions respond to competitive pressure and perceived expectations to appear technologically current (Dumitru et al., 2014). In AI-enabled pedagogy, this can evolve into metamimesis—an AI-mediated extension of imitation in which widespread use of similar models yields convergent instructional practices and student outputs. When identical models are deployed across courses, algorithmic generation can produce similar analytical narratives, code structures, and written responses even when prompts are individualized (Arthur, 2025).

To clarify the pedagogical stakes of this phenomenon, it is necessary to distinguish between code efficacy and insight efficacy through the lens of the Resource-Based View. Code efficacy refers to technical proficiency in executing routine analytical tasks, including syntax generation, debugging, and surface-level problem solving—domains in which LLMs have already demonstrated substantial performance gains. While these capabilities enhance efficiency, they do not, on their own, generate the heterogeneity required for sustained differentiation.

From an RBV perspective, reliance on code efficacy alone undermines the VRIN characteristics of human capital. If the primary outputs of instruction consist of analytical artifacts that can be readily reproduced by automated systems, the resulting competencies are neither rare nor difficult to imitate. Insight efficacy, by contrast, represents the interpretive capacity to evaluate, contextualize, and translate analytical outputs into strategic judgment. It is this form of human capital—rather than technical execution—that retains value in environments shaped by automation.

Within classroom practice, a pedagogical shift toward insight efficacy reframes assessment away from questions such as "How do I write this Python script?" toward "How do I interpret this model's behavior to inform a business decision?" This shift is increasingly necessary as technical proficiency becomes more easily replaced by AI tools. Without intentional instructional redesign, educational environments risk producing graduates whose analytical skills are vulnerable to automation rather than complemented by it.

Metamimesis poses a direct threat to this form of differentiation. When students rely on identical LLMs without the dynamic capabilities to interrogate, critique, and extend AI-generated outputs, learning outcomes converge. The result is a standardization of reasoning that contradicts the RBV's emphasis on heterogeneity. This creates a paradox: institutions may gain external legitimacy by visibly integrating AI technologies, yet simultaneously erode the internal differentiation that gives their graduates distinctive value.

Emerging empirical work suggests that structured, instructor-guided LLM use can produce stronger learning outcomes than unrestricted access, underscoring the importance of intentional curriculum and assessment redesign rather than tool availability alone.

Proposition Development

Proposition 1

The likelihood that LLM adoption is ceremonial—manifested through pedagogical decoupling and high variance in higher-order learning outcomes—is positively associated with the strength of mimetic and normative isomorphic pressures experienced by the educational institution.

Institutional Theory predicts that under conditions of heightened legitimacy pressure, organizations adopt visible structures that signal conformity rather than substantively altering internal practices. In educational settings, such pressures are amplified when peer institutions, accrediting bodies, or professional networks promote AI integration as a marker of modernity. Under these conditions, LLM adoption is more likely to function symbolically, resulting in superficial incorporation of AI tools that preserves formal compliance while leaving instructional design largely unchanged.

From a Resource-Based View, ceremonial adoption fails to generate sustained pedagogical value because it does not cultivate heterogeneous human capital. While AI tools may standardize access to technical outputs, they do not, in themselves, confer differentiation. Instead, differentiation depends on how faculty deploy these tools to develop interpretive and decision-oriented capabilities that remain difficult to imitate. Absent intentional instructional integration, LLM usage amplifies outcome variance across classrooms, reflecting uneven or opportunistic use rather than systematic pedagogical design.

Dynamic capabilities provide the mechanism through which this divergence occurs. Faculty who lack the capacity to sense meaningful pedagogical opportunities, seize those opportunities through redesigned instruction, and transform curricula in response to automation pressures are more likely to incorporate LLMs in ways that reinforce ceremonial compliance. Conversely, when such capabilities are present, faculty can redirect AI usage away from routine code execution toward the development of insight efficacy. Where dynamic capabilities are weak or unsupported, even well-intentioned AI adoption is likely to result in inconsistent learning outcomes and increased decoupling across instructional contexts.

Proposition 2

Higher levels of faculty dynamic capabilities related to LLM integration are associated with lower variance in higher-order learning outcomes, indicating substantive pedagogical integration and reduced decoupling.

While Institutional Theory explains why organizations may adopt AI symbolically, it does not account for variation in instructional outcomes across classrooms. The Resource-Based View and dynamic capabilities framework help explain this variation by shifting attention to faculty agency. In AI-enabled learning environments, faculty operate within institutional constraints that privilege standardization, accreditation compliance, and comparability. Yet within these boundaries, educators retain discretion over instructional design, assessment practices, and the pedagogical role assigned to AI tools.

Dynamic capabilities provide the mechanism through which faculty navigate this tension. Faculty with stronger capabilities to sense pedagogically meaningful applications of LLMs, seize those opportunities through instructional redesign, and transform curricula in response to automation pressures are better positioned to integrate AI substantively. In such contexts, LLMs are embedded systematically into learning activities that emphasize interpretive judgment, critical reasoning, and insight efficacy rather than routine task execution. As a result, learning outcomes become more consistent across students, reflecting intentional scaffolding rather than opportunistic or uneven AI use.

By contrast, when faculty dynamic capabilities are weak or unsupported, LLM adoption is more likely to be fragmented and inconsistent. In these cases, AI tools are appended to existing curricula without corresponding changes to assessment or learning objectives, producing high variance in higher-order learning outcomes. Such variance signals pedagogical decoupling: while AI is formally present, its instructional role is neither standardized nor aligned with intended learning goals.

Strategic Choice theory helps explain how faculty enact these dynamic capabilities under institutional constraint (Child, 1972). Strategic choice is not a binary decision between compliance and innovation, but an ongoing negotiation over how instructional practices can evolve while maintaining legitimacy (Child, 1972). Faculty vary in how they exercise this choice, giving rise to distinct patterns of AI integration.

One pattern is ceremonial compliance, in which faculty lack the sensing capability to distinguish pedagogically valuable AI applications from symbolic ones. LLMs are adopted primarily to satisfy administrative mandates or align with prevailing institutional narratives of innovation, resulting in superficial use and elevated outcome variance.

A second pattern is subversive innovation, in which faculty possess strong dynamic capabilities but face intense pressure to preserve traditional assessment formats. These educators may encourage informal AI use for learning while maintaining legacy evaluation practices to protect rational legitimacy. Although this approach enables learning gains, it produces a hidden curriculum that is difficult for institutions to observe, evaluate, or leverage as a distinctive resource.

These patterns set the stage for a third configuration—integrative transformation—which is developed in Proposition 3. In this ideal state, faculty exercise strategic choice by aligning institutional legitimacy requirements with pedagogical innovation, openly redesigning assessments to evaluate insight efficacy while preserving standards of academic robustness. Together, these configurations illustrate how faculty dynamic capabilities shape whether AI adoption results in decoupling or substantive educational transformation.

Proposition 3

Faculty who actively engage in strategic choice to balance institutional legitimacy requirements with the differentiation of student capabilities are more likely to contribute to the development of organizational capital than faculty who engage primarily in ceremonial LLM adoption.

Whereas Proposition 2 focuses on instructional outcomes at the classroom level, Proposition 3 extends the framework to the organizational level. When faculty exercise strategic choice to align macro-level legitimacy pressures with micro-level pedagogical innovation, the resulting instructional practices become embedded, replicable, and institutionally recognizable. Over time, these practices accumulate as organizational capital in the form of shared pedagogical norms, assessment models, curricular templates, and institutional learning around effective AI integration.

In contrast, ceremonial adoption of LLMs generates limited organizational learning. Because AI use in these contexts remains symbolic, inconsistent, or weakly coupled to learning objectives, it fails to produce transferable knowledge or durable instructional assets. As a result, institutions may appear technologically current without developing the internal capabilities required to sustain pedagogical differentiation or guide future innovation.

Taken together, these propositions articulate a multilevel framework in which institutional pressures shape adoption incentives, faculty dynamic capabilities determine instructional integration, and strategic choice governs whether AI-enabled pedagogy produces decoupling or accumulates as organizational capital. This framework explains how the same technology can yield superficial compliance in some contexts and substantive educational transformation in others.

Future Research Agenda (Operationalizing the Framework)

The agenda below is an operationalization guide for future empirical studies (not a grant-style proposal). It specifies measurable constructs and adaptable design options across programs and governance settings.

Operationalizing core constructs

• Institutional pressures / legitimacy signals: code accreditation language, program assessment policies, employer advisory feedback, and public AI initiatives; measure perceived comparability and integrity expectations via stakeholder surveys and policy content analysis.

• Ceremonial adoption / decoupling: measure policy–practice distance by comparing (a) stated AI policies and (b) assignment design, rubrics, attribution rules, integrity auditing, and grading practices.

• Faculty dynamic capabilities (sensing–seizing–transforming): operationalize via faculty AI-pedagogy training, redesign artifacts (assignment prompts, rubrics, integrity protocols), and reflective accounts of redesign decisions; triangulate with peer review of course materials.

• Insight efficacy outcomes: assess students' ability to interpret, critique, and apply analytical outputs (assumption checking, error analysis, decision justification) using performance tasks and calibrated rubrics; report both mean performance and within-section variance as a signal of coherence versus fragmentation.

Design options for theory testing (illustrative)

• Multi-section comparisons: examine whether sections with stronger redesign artifacts and clearer governance produce higher insight-efficacy performance and lower variance in higher-order outcomes.

• Qualitative case tracing: combine faculty interviews with course artifact analysis to identify strategic choice patterns (ceremonial compliance, subversive innovation, integrative transformation) and boundary conditions (e.g., accreditation stringency, departmental norms).

• Mixed-methods integration: link macro-level institutional signals (policies, legitimacy narratives) to micro-level pedagogy (rubrics/assignments) and student outcomes (insight efficacy).

Ethics, consent, and integrity guardrails

Future classroom-based studies should include informed consent (or IRB/ethics approval where applicable), transparency about AI tool use, privacy protections, and safeguards against coercion or grading-related pressure to participate. Studies should document integrity protocols (permitted vs. prohibited AI uses, attribution expectations, and auditing procedures) so findings are interpretable within a clear governance context.

Discussion and Conclusion: Governing AI-Enabled Pedagogy Beyond Ceremonial Compliance

This study develops a conceptual framework to explain why the integration of large language models (LLMs) in business education can yield either superficial compliance or substantive pedagogical transformation. The framework clarifies how identical technologies can produce markedly different educational outcomes across institutional contexts. In doing so, it extends existing work on AI-enabled pedagogy by shifting attention away from tools themselves and toward the organizational and pedagogical conditions under which those tools generate value.

A core implication of the framework is that ceremonial AI adoption is not merely a pedagogical failure but a governance problem. When institutions prioritize visible compliance with technological trends over the development of internal instructional capabilities, they risk decoupling formal structures from substantive learning outcomes. The framework highlights how such decoupling is reinforced when faculty lack the institutional support, incentives, or autonomy required to redesign assessment and instruction in response to AI-enabled automation. Under these conditions, AI integration may enhance the appearance of innovation while contributing little to higher-order learning.

Meaningful AI-enabled pedagogy, by contrast, depends on sustained investment in faculty dynamic capabilities. Educators who can sense pedagogically valuable applications of LLMs, seize opportunities for instructional redesign, and transform curricula to foreground interpretive judgment are better positioned to align institutional legitimacy with learning innovation. This alignment reduces outcome variance driven by opportunistic tool use and instead produces consistency rooted in intentional pedagogical design. Importantly, the framework emphasizes that such capabilities are not solely individual attributes but are shaped by governance structures, professional development pathways, and institutional norms.

Ultimately, the strategic future of AI-enabled business analytics education will be determined not by technological diffusion alone but by governance structures, faculty capabilities, and deliberate pedagogical design. Institutions that align legitimacy requirements with capability development will cultivate durable forms of human capital that remain valuable in AI-mediated environments. Those that prioritize symbolic compliance risk institutionalizing superficial innovation without substantive learning gains.

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