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AI Disruptions in Higher Education: Evolutionary Change, Not Revolutionary Overthrow

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ABSTRACT

This paper offered a systems-theoretical analysis of large language models (LLMs) in the context of higher education. It began by first clarifying the conceptual landscape, then introducing key definitions to frame LLMs, not as revolutionary threats, but as evolutionary developments, grounded in decades of natural language processing and machine learning. Then, it examined how the integration of LLMs prompted institutions to seek new forms of homeostasis, balancing innovation with stability through adaptive regulatory feedback loops.

Next, the analysis explored intersections with broader concepts such as agency, authorship, commodification, and cybernetic governance. It argued that LLMs act as boundary objects whose meanings are negotiated across educational, industrial, and policy domains. It then responded to critiques framing LLMs as epistemically corrosive or ethically destabilizing by emphasizing the role of institutional reflexivity in mitigating risks.

Finally, the study concluded that LLMs do not fundamentally disrupt the mission of higher education; instead, they reveal its structural inertia. Their integration highlights the need for recalibrated pedagogical and assessment frameworks on learning processes. Instead of resisting technological change, institutions should evolve into feedback-responsive ecosystems that uphold human-centered values while embracing permissible forms of automation to enhance, rather than displace, intellectual and creative engagement.

Keywords: AI Integration in Higher Education, Disruptive vs. Evolutionary Innovation, Ethical Artificial Intelligence Governance, Homeostasis and Cybernetics, Human-AI Collaboration in Education, Large Language Models (LLMs), Systemic Adaptation to AI.

1. INTRODUCTION

Large Language Models (LLMs)[1] represent one of the most visible and consequential technological disruptions in American higher education in recent decades. While some view this disruption[2] as a revolutionary collapse of academic norms, this paper argues it is better understood as an *evolutionary systemic shift*,[3] one that compels institutions to recalibrate their pedagogical practices, assessment strategies, and epistemic assumptions in search of a new systemic equilibrium.[4]

The locus of this disruption lies in the changing relationship between student mastery and traditional forms of assessment. Assignments once designed to measure original thought, particularly essays, are increasingly undermined by LLMs' capacity to generate persuasive, grammatically polished, and contextually appropriate text. For many students, these tools function not merely as supports but as *substitutes* for cognitive engagement. As a result, educators face a pressing challenge: how can we assess authentic understanding when machines can simulate it so convincingly?

Recent critiques from Victoria Livingstone [2] and James D. Walsh [3] sharpen this dilemma. Livingstone laments that students now bypass the productive discomfort required for intellectual growth, instead outsourcing their thinking to AI tools. Walsh documents the rise of AI-assisted cheating as a normalized behavior, one that shows the erosion of both academic integrity and pedagogical purpose, these perspectives, while valid and deeply concerning, risk misattributing the crisis to student behavior alone. In reality, they expose a broader institutional failure to adapt to epistemological and technological change,[i] and to transform educational practices [4].

The gradual normalization of AI-assisted "cheating" did not emerge fully formed; rather, it has crept into academic practice through an incremental delegation of tasks once deemed trivial

[1] **LLM (Large Language Model):** A type of artificial intelligence trained on massive text data to generate human-like responses. Examples include GPT-4 and Gemini [1].

[2] **Disruption:** A systems-level disturbance that challenges existing norms, structures, or practices. Often shows deeper fragilities rather than causing them outright.

[3] **Evolution (Systemic):** Gradual transformation in a system through feedback and adaptation, in contrast to sudden revolutionary change.

[4] **Systemic Equilibrium or Homeostasis:** A state of dynamic balance in a system achieved through feedback and adaptation, not stasis. In education, it refers to institutional stability amid technological change.

yet essential for developing student mastery. At its inception, the use of tools like Grammarly to correct grammar or polish prose seemed innocuous, a convenience that saved students a few minutes on a skill that grade-school curricula long ago trained them to perform unassisted. Nevertheless, by outsourcing even this rudimentary task, learners began to internalize a simple calculus: if a machine can do it faster and with less effort, why expend their cognitive resources?

From this first almost imperceptible step, the threshold of permissible automation has steadily shifted. The next frontier comprised low-stakes writing tasks, such as brief responses to readings, discussion-board posts, or comprehension questions. These assignments require only minimal original thought, a paraphrase of the prompt, a cursory glance at the source text, and a sentence or two of explanation. What once took a diligent student five or ten minutes of reflection and drafting is now generated in seconds by an LLM. As reports of AI-facilitated shortcuts illustrate, students rapidly came to treat these small assignments not as exercises in thinking but as convenient data-entry tasks for an algorithm.

It is only a short rhetorical leap from these micro-tasks to full-scale essay production. Early adopters of LLM-generated essays were easy to spot, with stilted prose, formulaic arguments, and an absent student voice. However, as models improved, their outputs became virtually indistinguishable from genuine student writing, with well-structured arguments, persuasive language, and alignment to rubric criteria. Faced with this level of quality, students asked themselves the same question posed by children who eschew manual calculations in favor of a calculator: "Why bother?" If an AI can compose an entire paper in seconds, editing and drafting become vestigial skills in the student's eyes.

This progression points to a paradigm shift: tasks once scaffolded to build foundational competencies have been hollowed out by ambient linguistic productivity[5]. What began as a benign grammar check has, step by step, evolved into wholesale intellectual substitution, transforming learning into prompt engineering. In the eyes of today's students, it is far more valuable to master the art of eliciting sophisticated AI outputs than to engage deeply with the craft of writing itself. This trajectory, which moves from surface-level editing to complete authorship replacement, not only normalizes academic misconduct but also signals an urgent need for pedagogical redesign that restores genuine effort and agency within an ecosystem where machines increasingly surpass human capabilities.

This paper advances a systems-level perspective that LLMs are neither inherently destructive nor inherently emancipatory. Instead, they act as catalysts that *expose the fragility* of legacy practices in a digitized learning environment. The appropriate institutional response is not resistance, but redesign, rethinking learning ecosystems in ways that preserve intellectual rigor, foster agency, and adapt assessment to reflect a world where linguistic productivity is ambient, not exceptional.

1.1. LLMs as disruptive innovation

LLMs are not merely tools that students use to evade cognitive effort; they are technological agents that reconfigure the entire ecology of learning, instruction, and institutional assessment. Their influence now extends beyond the classroom into curriculum design, faculty labor, and educational policy. Educators are increasingly experimenting with generative AI[6] tools powered by LLMs as formative feedback engines, adaptive tutors, and research co-processors. Yet these explorations exist alongside widespread misuse. As Walsh [3] points out, many students treat AI as an academic shortcut, employing it to generate essays, paraphrase text, or launder content through iterative prompts to avoid detection. Such practices erode the cognitive effort that gives rise to scholarly rigor.

Livingstone [2] identifies a more acute epistemological shift: students increasingly outsource the recursive, meaning-making process of writing, the "hundreds of small choices" through which academic voice and critical thinking emerge. When authorship becomes a function of machine suggestion rather than internal deliberation, the university risks abandoning its central purpose: cultivating intellectual autonomy through disciplined struggle.

However, the prevalence of misuse should not be mistaken for an indictment of the technology itself. Instead, it brings out an institutional lag. Students resort to generative AI tools in part because pedagogical structures remain premised on conditions of linguistic scarcity and linear authorship, conditions no longer reflective of the current information ecosystem. The true disruption, then, is not generative AI itself, but the absence of adaptive regulatory systems capable of integrating it constructively.

When introduced without systemic reflectivity, LLMs function like malfunctioning switches on a railroad, a metaphor Wiener evokes through the signalman misled by faulty cues,[7] highlighting the dangers of unintegrated automation. The breakdown occurs not because the tool exists, but because the feedback loop[8] between intent, action, and evaluation is either missing or corrupted. Likewise, current educational structures often lack the institutional mechanisms necessary to interpret the "actual state" of student learning in a world mediated by generative AI.

1.2. Systems view of LLMs

Technological change often masquerades as revolution when, in fact, it constitutes a process of systemic adaptation, resistance, and integration. Large Language Models (LLMs) are best understood not as existential threats, but as accelerants of long-standing tensions in higher education: the divide between learning and credentialing, the erosion of intrinsic motivation, and the commodification of intellectual labor. As both Livingstone [2] and Walsh [3] illustrate, AI has not caused these crises, but rather magnified existing institutional vulnerabilities.

Much of the public anxiety surrounding large language models stems not from their present capabilities but from a misdirected fear that they are rapidly evolving into far more powerful

[5] **Linguistic Productivity:** The ability of a language to generate novel words, phrases, or sentences using a finite set of rules and elements.

[6] **Generative AI:** AI systems that produce content (text, images, code, etc.) based on learned patterns. ChatGPT is a generative AI tool powered by an LLM [5].

[7] This metaphor draws directly from Norbert Wiener's foundational work in cybernetics, where he emphasizes the vulnerability of automated systems when feedback loops are poorly integrated or misaligned. The malfunctioning switch exemplifies a broader principle in technical systems theory: without contextualized governance, even precise subsystems (like LLMs) can propagate systemic error [6].

[8] **Feedback Loop:** A system mechanism where output is monitored and reintegrated to adjust future behavior. Essential for adaptation and learning.

intelligences. This conflation resembles the classic fallacy of misplaced concreteness, in which concerns about a hypothetical future threat are erroneously projected onto a current phenomenon. It is like insisting that a machine programmed with the sole objective of maximizing paperclip production might eventually decide to eliminate humanity to access more resources [7]. In reality, LLMs remain specialized pattern-matching engines with no genuine understanding or autonomous goals.

The discourse of "existential risk" in AI traditionally addresses scenarios in which a system's objectives diverge catastrophically from human interests (scenarios predicated on self-improving, goal-directed agents). No current LLM exhibits the recursive self-modification or long-term planning abilities that underpin such theoretical risks. To treat their limitations as evidence of impending superintelligence is to commit a category error that conflates tool-level performance with agent-level autonomy. If we are worried about superintelligence, our attention should be on architectures explicitly designed for goal pursuit and self-enhancement, not on today's text-generation APIs.

Similarly, economic anxieties such as job displacement are often lumped together with existential concerns, further muddying the debate. While it is valid to explore how automation may reshape labor markets, this is a distinct question from whether LLMs might someday threaten human survival. Mixing these issues under the single banner of "AI risk" dilutes both discussions and impedes targeted policy responses. We need separate frameworks for evaluating short- to medium-term economic impacts and speculative long-term agency risks.

By disentangling these threads, we can focus our efforts where they matter most. Recognizing the category error in equating LLMs with AGI allows educators and policymakers to address real, present-day challenges such as academic integrity, equity in access, and pedagogical redesign without being sidetracked by speculative fears. In doing so, we preserve the possibility of harnessing LLMs constructively while reserving existential-risk discussions for genuinely agentive AI systems yet to be realized.

This paper argues that LLMs belong to a broader evolutionary trajectory in which educational systems must seek new points of equilibrium. The imperative is not to preserve outdated forms of instruction or assessment for tradition's sake, but to reimagine structures of agency, authorship, and evaluation for an age where linguistic productivity is ambient, iterative, and machine-augmented.

From a systems-theoretical perspective, LLMs function as boundary objects,[9] entities that traverse multiple domains (e.g., education, industry, policy) and whose meanings are negotiated across divergent institutional logics. Their presence compels institutions to confront foundational questions:

Q1: How do we balance innovation with accountability?

LLMs are evolving faster than the ethical, legal, and pedagogical frameworks meant to regulate them. In business, they amplify efficiency but may obscure responsibility and amplify bias. In education, the threat is epistemological, risking the substitution of simulation[10] for learning, and convenience for reflection [8]. The issue is not whether LLMs should be adopted, but how to design feedback systems that can regulate their use responsibly, preserving human-centered values while leveraging their affordances [9].

Here, Norbert Wiener's *Cybernetics*[11] provides a noteworthy insight. Effective systems, Wiener argues, require more than potent effectors; they must include feedback loops that monitor and adjust outputs in real time. As he explains: "[…] for effective action on the outer world it is not only essential that we possess good effectors, but that the performance of these effectors be properly monitored back to the central nervous system […]" [6, p. 96]. In the educational context, this means designing institutional mechanisms that continuously assess how LLMs are used, not merely by students, but across faculty, policy, and administration, so that pathways can be adjusted through informed policy decisions and responsive governance.

Q2: How do we reconcile the divergent goals of business and education in AI adoption?

What cybernetics teaches us is that systems endure not by resisting change, but by absorbing novelty through adaptive regulation.[12] Institutions of higher education must therefore transition from static rule-enforcement models to dynamic, feedback-responsive ecosystems, capable of interpreting new behaviors and adjusting goals in real time. Adopting such adaptive, feedback-driven models constitutes not a surrender to technology, but an evolution of institutional purpose.

Before proceeding to specific frameworks or policy interventions, it is essential to establish a shared vocabulary. As this paper engages in a systems-theoretical analysis of Large Language Models within higher education, clarity in key definitions is necessary. Terms such as "disruption," "evolution," "agency," and "feedback" carry layered meanings across disciplines, from education and ethics to cybernetics and information theory. Without precise articulation, these terms risk becoming metaphorical stand-ins rather than analytical tools. Therefore, the following section provides working definitions that will anchor the subsequent arguments, enabling conceptual rigor and facilitating transdisciplinary dialogue.

1.3. Situating the inquiry

Before proceeding to define key concepts, it is important to situate this inquiry within a systems-theoretical framework. The challenges posed by Large Language Models (LLMs) are not confined to technological affordances or pedagogical tools; they are symptoms of deeper tensions within the institutional logic of higher education. LLMs operate as boundary technologies that traverse disciplines, policies, and epistemic assumptions, generating pressures that expose system-level fragilities. The significance of their impact lies not in their novelty alone, but in how they interact with and amplify existing structural inefficiencies. In the same way that a magnifying glass does not create imperfections on a surface, but rather, it makes existing flaws more visible and pronounced, LLMs do not introduce new inefficiencies, but rather, interact with and amplify those already present within institutional structures.

[9] **Boundary Object:** A concept or tool that moves between domains, taking on different meanings while linking stakeholders.

[10] **Simulation** refers to generating plausible responses; understanding involves conceptual depth, contextual awareness, and intentional reasoning.

[11] **Cybernetics:** The study of control and communication in complex systems through feedback was pioneered by Norbert Wiener. Forms the basis for system regulation in this paper.

[12] **Adaptive Regulation:** The ongoing ability of a system to adjust rules, behaviors, or goals in response to internal and external changes.

A systems-theoretical lens allows us to move beyond binary responses of panic or celebration. Instead, it frames LLMs within the dynamics of feedback loops, control structures, emergent properties, and institutional adaptation. From this perspective, LLMs are understood not merely as tools used or misused by students but as integral actors within a complex ecology of cognition, labor, and legitimacy. Their influence shapes how knowledge is produced, validated, and valued.

As Barman, Caron, Claassen, and de Regt [10] argue, genuine scientific understanding, whether in humans or machines, requires more than accurate output. It depends on the capacity to *explain*, *contextualize*, and *anticipate*. Likewise, Les and Les [11] emphasize that understanding is not reducible to performance but must involve interpretability[13] and model-based reasoning. According to Neil J. Dorans, "authentic assessment requires collecting real data through well-designed experiments that test hypotheses about nature" [12]. These insights reinforce the need to examine LLMs not merely as functional tools but as epistemic actors whose outputs challenge our core assumptions about what it means to know, to understand, and to explain.

2. BASIC DEFINITIONS

In systems thinking, particularly when examining responses to external pressures and disruptive events, equilibrium, adjustment, and evolution describe distinct yet interrelated modes through which a system responds to change and undergoes transformation, often at incremental or localized levels. In other words, equilibrium refers to the tendency of a system to maintain or return to a balanced state. Adjustment is the act of restoring that balance after a disturbance, typically by reintegrating the disruptive influence or enduring its effects, thereby returning to a prior state of functional stability. Evolution, by contrast, involves a more fundamental transformation into a new configuration or an entirely different kind of system, often catalyzed by prolonged disruptions.

These are not always discrete phases; a system may undergo adjustment and evolution simultaneously. Evolution within a system tends to be slow and incremental, operating holistically to enhance the system's adaptive capacity over time.

By contrast, a revolution denotes a sudden, complete, and foundational transformation of a system. It typically involves the displacement or replacement of existing structures, ideologies, or processes with new ones. Revolutionary change seeks a radical break from the past. It often introduces instability as old paradigms are dismantled and new frameworks of thought, method, structure, or belief are imposed or adopted.

2.1. Core terms for systemic interpretation of AI in higher education

This section defines key terms essential for analyzing the impact of LLMs within higher education through a systems-thinking lens. Concepts such as disruption, evolution, agency, and feedback are explored not in isolation, but as interdependent components of complex sociotechnical systems.[14] By clarifying these terms, the section establishes a conceptual foundation for understanding how AI technologies challenge traditional educational structures and catalyze institutional responses. These definitions are situated at the intersection of cybernetics, pedagogy, and organizational adaptation, offering a shared vocabulary to support transdisciplinary dialogue and guide systemic reform.

The following core terms provide conceptual anchors for interpreting systemic responses to AI in educational institutions.

2.1.1 Disruption: In the context of higher education and sociotechnical systems, *disruption* refers to the introduction of a tool, process, or condition that fundamentally alters existing patterns of behavior, organization, or value production. As framed by Clayton M. Christensen [13], disruptive innovation often begins by offering simpler, more accessible alternatives, later displacing established models. In this paper, disruption is examined as a systems-level disturbance that shows latent structural tensions, particularly between pedagogy, assessment, and automation.

2.1.2 Evolution: Evolution denotes gradual, non-linear adaptation over time through selective pressures, feedback loops, and emergent complexity. Drawing from both biological and systems theory traditions, it implies continuous change driven by environmental interaction and internal adjustment rather than abrupt transformation. Within this study, evolution is understood as the institutional recalibration of higher education in response to LLMs, not a collapse of form, but a reorganization of function.

2.1.3. Agency: Agency describes the capacity of an actor, human or nonhuman, to initiate and effect change within a given structure. In sociotechnical systems, agency is distributed; it may emerge through the interaction of humans, algorithms, and institutional norms. This paper distinguishes between *epistemic agency*[15] (the ability to think, interpret, and know) and *instrumental agency*[16] (the power to act within constraints). The challenge posed by LLMs is precisely that they blur the boundaries between human intention and machine execution.

2.1.4. Feedback: Feedback is a regulatory mechanism within dynamic systems whereby outputs are monitored, evaluated, and reintegrated into the system to adjust future actions. As Wiener [6] explains in *Cybernetics*, effective feedback ensures a proportional and adaptive response to change. Positive feedback amplifies deviations; negative feedback stabilizes equilibrium. In educational contexts, feedback includes not only evaluative comments but institutional responses to emergent student behavior, including the use (or misuse) of AI tools. The failure to implement responsive feedback loops is, arguably, the primary reason LLMs feel disruptive rather than integrative.

To deepen the systems-level framework introduced above, it is necessary to return to the conceptual roots of cybernetics. This section explores the term's etymology and classical usage, establishing a philosophical foundation for its application in

[13] **Interpretability:** The extent to which a machine-generated output can be understood, explained, and justified by human users or evaluators.

[14] **Sociotechnical System:** A system that includes both social (human, institutional) and technical (machine, algorithmic) components. Education is treated here as a sociotechnical system.

[15] **Epistemic Agency:** Epistemic agency refers to the capacity to think and understand.

[16] **Instrumental Agency:** Instrumental agency refers to the ability to act. LLMs blur these boundaries.

educational governance and AI integration.

2.2. Key Concepts in Cybernetics: Etymology and Greek Definition

The term *cybernetics* originates from the Greek word **κυβερνητική** (*kybernētikē*), which means "the art of steering" or "governance." It is derived from **κυβερνήτης** (*kybernētēs*), meaning "steersman," "pilot," or "governor." This etymology reflects the discipline's focus on systems control, regulation, and guidance, emphasizing purposeful direction within complex systems.

Norbert Wiener popularized the term in his seminal work *Cybernetics, Second Edition: Or Control and Communication in the Animal and the Machine* [6], applying it to the study of systems that involve feedback and communication to maintain stability or achieve goals.

The following four concepts, feedback, control, regulation, adaptation, and emergent properties, form the foundational grammar of cybernetic systems thinking and will serve as tools in our analysis of AI's impact on education.

2.2.1. Concept I–Feedback: refers to the process by which a system monitors the outcomes of its actions and uses that information to adjust future behavior. It is foundational to system self-regulation, learning, and adaptation.

- **Positive feedback** amplifies changes, pushing the system further from its current equilibrium and often accelerating divergence or instability.
- **Negative feedback** reduces deviations, counteracting disturbances and stabilizing the system by promoting a return to equilibrium.

In cybernetic systems, effective feedback loops are essential for resilience, responsiveness, and systemic learning over time.

2.2.2. Concept II–Control and Regulation: Control involves the deliberate steering of a system toward specific goals, states, or outcomes. It is typically exercised through planned interventions, feedback loops, and real-time monitoring. Regulation refers to the internal processes that maintain order, consistency, and responsiveness within the system, often independent of direct external control.

In cybernetic terms, control and regulation are intertwined: while control defines directionality, regulation ensures operational coherence. In educational systems, this interplay becomes evident in curriculum design (control) and academic policy enforcement (regulation), both of which must now account for the dynamic influences of AI.

2.2.3. Concept III–Adaptation: Adaptation is the capacity of a system to modify its structure, behavior, or internal processes in response to internal shifts or external pressures. It can occur through:

- **Incremental learning** (adjustment),
- **Structural transformation** (evolution), or
- **Rapid recalibration** (in response to disruption).

Adaptive systems are characterized by flexibility, memory, and feedback integration. In the context of LLMs, institutional adaptation involves rethinking assessment design, faculty roles, and mechanisms of epistemic validation to reflect changing conditions.

2.2.4. Concept IV–Emergent Properties: Emergent properties are system-level characteristics or behaviors that arise from the interaction of components in ways that cannot be deduced from the properties of individual parts. They include unexpected capabilities, patterns, or behaviors that surface only through systemic complexity.

In evolutionary change, emergent properties often reflect new configurations that improve resilience or performance. In revolutionary change, emergence may disrupt identity, leading to unpredictable and sometimes irreversible shifts. Recognizing emergence is necessary for understanding non-linear change, especially in complex sociotechnical systems where LLMs can produce both innovation and instability simultaneously.

Having outlined the foundational concepts of cybernetics, feedback, control, regulation, adaptation, and emergence, we now turn to one of its most integrative and enduring principles: homeostasis. Often invoked to describe biological or mechanical equilibrium, Homeostasis in complex systems extends far beyond balance alone. It captures the dynamic interplay of stability, responsiveness, and internal coherence, particularly under conditions of sustained external change. Understanding homeostasis is important for analyzing how educational systems respond to the presence of LLMs, not simply by resisting disruption, but by reorganizing around it.

2.3. Systemic resilience and homeostasis

Homeostasis refers to a state of dynamic equilibrium in which a system maintains internal stability while navigating external fluctuations. It is not a condition of stasis, but one of continuous regulation, achieved through feedback loops that detect deviations and activate corrective responses. These mechanisms allow the system to operate within optimal parameters, sustaining coherence without collapsing under pressure.

Control plays a central role in this process [14]. It involves guiding the system toward desired goals or states, often through strategic decision-making informed by real-time feedback. Regulation, closely related, comprises the internal processes that uphold balance and manage responses to disruption. Together, control and regulation enable a system to function adaptively while preserving identity and continuity.

Crucial to this understanding is the role of emergent properties, characteristics, or behaviors that arise not from any single component but from the complex interactions among parts. These properties cannot be fully anticipated through reductionist analysis and are essential to interpreting both evolutionary and revolutionary change. Without accounting for emergence, systemic transformation is likely to be misread as either accidental or anomalous.

In evolutionary contexts, emergent properties may confer adaptive advantages, novel functions, or structures that increase resilience or enable survival under new conditions. In revolutionary moments, however, the emergence of radically new dynamics can lead to the reorganization, destabilization, or even collapse of a system's core functions and identities. These transformations underscore the importance of viewing systems not as fixed architectures but as living, interacting totalities.

To fully comprehend change within complex systems, one must look beyond isolated components or static snapshots. The real impact of disruption, such as that introduced by LLMs, can only be understood by examining the system-wide interactions over time, where new patterns, capabilities, and vulnerabilities emerge. Recognizing the potential for emergence is thus fundamental to anticipating the non-linear, and often unforeseen, outcomes that characterize both systemic resilience and systemic failure.

3. LLMS: EVOLUTIONARY STEP, NOT A REVOLUTION

Revolutions, by their nature, involve abrupt and often destabilizing shifts, disruptions that tear through existing paradigms and demand wholesale systemic replacement. They are driven by deliberate, often ideological choices that seek rupture, not continuity. In contrast, evolution describes a more gradual, adaptive, and integrative process. It builds upon the foundations of what already exists, introducing change through iteration and recalibration. Within this framework, LLMs represent not a revolution, but an evolutionary step, albeit one that accelerates adaptation at speeds never seen before.
To examine this evolutionary nature more closely, the following subsections analyze how LLMs extend and amplify prior technological trajectories rather than displacing them. The first subsection discusses the historical continuity of LLM development as a cumulative process grounded in decades of progress in natural language processing and machine learning. The second subsection considers how the perceived disruption of LLMs is better understood as a catalyst for accelerated adaptation, reshaping existing systems rather than dismantling them.

3.1. Building on existing systems

LLMs are not isolated inventions but the result of cumulative advances in natural language processing (NLP), machine learning, and artificial intelligence. Their capabilities, contextual understanding, coherent language generation, and adaptive interaction extend rather than rupture prior technological progress. They emerge from decades of iterative refinement, reflecting the trajectory of computational linguistics and deep learning architectures.
Unlike revolutionary technologies that dismantle and reconstruct systems wholesale, LLMs operate by augmenting and optimizing current infrastructures. Their influence is additive and integrative: improving workflows, expanding access to information, and enabling new forms of creativity and communication. In education, for instance, LLMs support personalized learning pathways but do not replace core pedagogical principles. Instead, they complement traditional approaches by enhancing formative assessment, tutoring, and curriculum scaffolding.

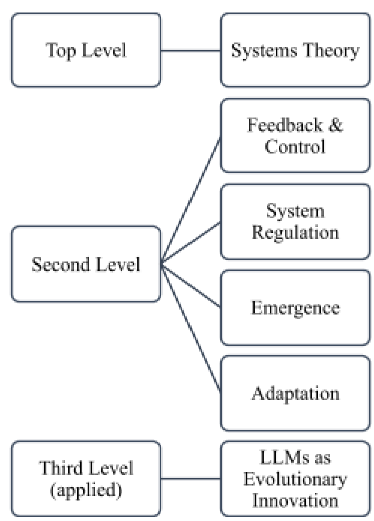
3.2. Adaptation versus disruption

Historically, technologies like the printing press and the internet were initially viewed as disruptive, but they ultimately catalyzed systemic adaptation and long-term integration. LLMs follow a similar trajectory: while they introduce rapid changes, their enduring impact will hinge on the capacity of institutions, educators, and policymakers to adapt existing structures accordingly [15].
LLMs exemplify adaptive innovation; they modify how we perform tasks without wholly redefining the systems themselves. While they exhibit some characteristics of disruptive technologies, their transformative potential is most evident in how they accelerate existing trends rather than initiate entirely new ones. The central challenge lies in the temporal mismatch: LLMs evolve through data and feedback loops at a pace much faster than institutional or human adaptation typically allows.
By improving tasks such as content generation, customer interaction, and data analysis, LLMs serve as force multipliers for human capabilities. Their capacity for domain-specific tuning, user personalization, and continuous learning makes them responsive tools for dynamic environments. Importantly, this responsiveness is not autonomous; it is contingent on how humans implement, regulate, and contextualize their use.
Ultimately, LLMs possess no intrinsic agency. Their function and influence are circumscribed by human intention and institutional frameworks. While their application may lead to unintended consequences, these outcomes arise from the systems within which they operate, not from the models themselves. In this sense, LLMs remain evolutionary tools: capable of accelerating transformation, but only within the limits and opportunities established by the human systems that wield them.[ii]

3.3. Visualizing this framework

Figure 1 presents a three-tiered hierarchical model that conceptualizes the integration of LLMs within sociotechnical systems. The Top Level grounds the framework in systems theory, establishing the foundational lens through which complex structures and behaviors are interpreted. The Second Level unpacks intermediary constructs, feedback and control, system regulation, emergence, and adaptation, which mediate between abstract theory and concrete implementation. These concepts are essential to understanding how systems evolve, maintain stability, and respond to disruption. The Third Level (applied) anchors the model in practice by framing LLMs as evolutionary innovations, tools that operate within existing systemic logics rather than dismantling them. Rather than depicting causal arrows, the figure emphasizes conceptual flow, illustrating how institutions can move from theoretical understanding to actionable design by aligning technological adoption with system dynamics. This hierarchical approach supports a structured, reflexive pathway for integrating LLMs in a way that enhances rather than destabilizes educational and organizational ecosystems.

Figure 1.- *From Theory to Practice: A Hierarchical Model of LLM Integration*



4. LLM AND THE PATH TO HOMEOSTASIS

Homeostasis, derived from cybernetic principles, describes a system's ability to regulate itself and achieve balance in the face of external changes.[iii] Within this framework, the integration of

LLMs does not signify permanent systemic destabilization. Rather, LLMs represent a catalytic force prompting recalibration toward a new equilibrium. This section explores how feedback, human-machine coexistence, and the pursuit of social equity through AI coalesce to sustain systemic balance.

4.1. Feedback Loops in Systemic Adaptation

Most LLMs do not adapt in real time; instead, they rely on iterative feedback loops in which user interactions and evaluation data are periodically aggregated and incorporated into controlled retraining cycles to improve outputs over time. At the same time, they participate in an ongoing Cybernetic process: societal regulations, workflows, and risk-mitigation strategies are continuously recalibrated in response to AI performance and impacts.

Haraway's seminal work [16] conceptualizes the cyborg not as a destabilizing anomaly but as a figure of hybrid stability. LLMs, like cyborgs, blur boundaries between human and machine in ways that invite reconfiguration rather than collapse. Fedorets et al. [17] also highlight the cognitive integration between humans and AI, emphasizing the emergence of co-adaptive systems. In such arrangements, feedback is not merely technical but socio-cognitive, involving reciprocal influence on human behavior, trust, and system design. Haraway's inspired deeper critiques regarding the interaction of identity, embodiment, and power in technological systems. Landström [18] interrogates the heteronormative assumptions embedded in feminist constructivist technology studies, revealing how gender co-produces technology and vice versa. This queering of feminist technology studies pushes the conversation beyond binary models and emphasizes feedback as relational, contested, and situated.

Goldenberg [19] complicates the notion of stable categories such as "woman," arguing that efforts to create universally applicable identity groups inevitably exclude marginalized experiences. Hofstede et al [20] explore the cultural dimensions and implications of these categories in several countries. When applied to AI and LLM systems, this critique foregrounds the necessity of designing feedback loops that do not presume homogeneity among users or beneficiaries but instead embrace pluralism and ambiguity.

Kinsley [21], drawing on Mitchell's urbanist vision, emphasizes the emergent Cyborg Self within digitally networked environments, where feedback includes not only data transmission but socio-spatial negotiation. This view situates LLMs within everyday infrastructures of connection and control, where affective, spatial, and systemic feedback loops are increasingly entangled.

Myers [22] adds a dimension to this by engaging with Indigenous epistemologies and critiques of property-based ontologies. Her discussion of objectification and cultural production suggests that LLMs, if embedded within dominant feedback economies, risk reproducing extractive paradigms. Responsive design must therefore account for relational ontologies and the situated ethics of knowledge exchange.

Together, these perspectives reveal that feedback in LLM systems is not merely a technical feature but a political and cultural dynamic. Addressing these complexities is essential for building adaptive, inclusive, and ethically grounded AI infrastructures.

4.2. Coexistence with Human Expertise

Rather than rendering human roles obsolete, LLMs redistribute cognitive labor. They assume repetitive or process-driven tasks, thereby freeing human actors for creative, ethical, and strategic functions. The premise aligns with Anderson and Anderson's [23] machine ethics proposition: autonomous systems should be guided by, and evaluated through, embedded ethical frameworks that center human values.

Cognitive integration with LLMs also foregrounds the idea of augmented rather than diminished agency. According to DiMatteo et al. [24], ethical AI governance involves sustaining human oversight, especially in domains of risk and public interest. Thus, coexistence demands hybridized work environments where AI assists but does not autonomously dominate, offering a viable model for techno-social harmony.

4.3. Equilibrium Through Participation and Representation

Equity, inclusion, and justice are central to any homeostatic rebalancing of sociotechnical systems. Drawing on Haraway's feminist technoscience, situated knowledges and epistemic plurality serve as essential mechanisms for resisting hegemonic AI regimes and mitigating systemic bias and inequity. To advance these aims, transparency and accuracy must guide the refinement of large language models, ensuring that their development aligns with principles of fairness and accountability. By democratizing access to generative tools, LLMs can amplify marginalized voices, provided their integration is guided by inclusive design.

In the context of refining LLMs to support equity, inclusion, and justice, transparency refers to the clear, accessible, and systematic disclosure of how these models are designed, trained, evaluated, and deployed. It entails making visible the underlying data sources, assumptions, training procedures, model architectures, heuristics, and limitations, so that stakeholders, researchers, policymakers, and the public, can scrutinize and understand the factors shaping model outputs. In particular, transparency about how the model is trained and which heuristics it applies during inference is critical, as these choices directly influence the emergence and perpetuation of biases.

Transparency, in this sense, serves several functions: it enables critical assessment of potential biases embedded in training data and heuristics, supports reproducibility and accountability in development, and empowers diverse communities to participate meaningfully in decisions about AI systems. As a practice grounded in epistemic plurality, transparency resists the opacity of "black box" AI regimes by fostering informed, participatory oversight and reducing the asymmetries of power and knowledge that often sustain inequity.

However, Estrada [25] warns of a new posthuman risk: the ideological entrenchment of human supremacy within AI structures, which can reinforce exclusion if not interrogated. He warns that invoking "the human" as an unexamined ethical anchor in AI policy can function as a "cheap proxy for ethical integrity," masking deep ideological commitments (human-supremacist rhetoric) without ever specifying whose interests count as "human". He shows that initiatives that claim to be "human-centered" all frame artificial systems as inherently subordinate to an undefined, monolithic "human". The core risk Estrada identifies is the classification of agents by type: by declaring certain entities (artificial or nonhuman) outside the moral category of "human," policies both legitimize an underclass of machine "slaves" and, by extension, can excuse the continued marginalization of human groups deemed "other." In effect, this binary boundary-making entrenches existing hierarchies under the guise of universalism. Estrada argues that appeals to "human-centeredness" therefore do not guarantee inclusivity; instead, they reinforce exclusion unless we interrogate who is framed as "human" and why. Pluhar [26] similarly critiques *speciesist moral hierarchies*[17] and urges us to consider the broader ethical spectrum when designing and deploying AI. From this view, AI equilibrium is not achieved through access alone but through representational justice and value-sensitive innovation.

As these insights illustrate, the systemic integration of LLMs hinges on achieving dynamic balance through ethical governance, equitable design, and adaptive coexistence. Yet, understanding LLMs solely through the lens of cybernetic regulation is not enough. Their influence intersects with broader conceptual terrains, including planetary equilibrium, ecological thinking, and sociopolitical representation. The following section extends the analysis by connecting homeostatic theory with the principles of diversity, equity, and inclusion (DEI), reframing them not as ancillary goals but as structural conditions for long-term systemic resilience.

5. KEY INTERSECTIONS WITH BROADER CONCEPTS

5.1. Homeostasis and DEI

As James Lovelock proposed in the Gaia hypothesis [28], [29], Homeostasis is the self-regulating process that maintains equilibrium in Earth's systems. If DEI is introduced into this context, it suggests that diversity in perspectives, equity in resource allocation, and inclusion in decision-making strengthen the system's ability to maintain balance. Diversity introduces variability and resilience, equity ensures fair access to resources for sustainability, and inclusion encourages systemic alignment and cooperation.

- **Idea:** DEI principles can enhance a system's self-regulating ability by introducing flexibility and resilience, promoting survival amid disruptions.
- **Analysis:** Diversity parallels ecological biodiversity, which supports adaptability. Equity and inclusion ensure fair access to resources, strengthening systemic balance.

5.2. Homeostasis vs. Disruptive Innovation

Disruptive innovation often functions by unsettling existing norms, catalyzing shifts in behavior, policy, or infrastructure. However, such disturbances are not inherently destructive. Within cybernetic and evolutionary frameworks, disruption can be reinterpreted as a phase that prompts a new homeostatic state. Systems capable of absorbing change without disintegration achieve greater long-term resilience.

In this light, LLMs serve not as harbingers of chaos but as agents of systemic evolution. Their successful integration depends not on resistance to change, but on the proactive cultivation of adaptive capacity within institutions, policies, and cultural practices. A balanced system must maintain stability while remaining open to innovation, a dynamic equilibrium between epistemic inertia[18] and transformation.

[17] **Speciesism** denotes the belief or practice of assigning different moral worth to beings solely on the basis of their species, often favoring humans over non-human animals. According to Wikipedia "Speciesism is a term used in philosophy regarding the treatment of individuals of different species". The term has several different definitions [27].

[18] **Epistemic Inertia:** The institutional tendency to preserve outdated knowledge systems or assessment methods despite changing conditions.

5.3. "Evolve or Die"

This phrase underscores a Darwinian imperative often invoked in technological and institutional contexts. In complex systems, survival depends not on preservation of the status quo but on sustainable adaptation to shifting environments. LLMs exemplify this principle: they support medium-term adaptation by enhancing decision-making, communication, and problem-solving without uprooting foundational structures.

Rather than triggering an abrupt revolution, LLMs accelerate evolutionary change. They represent a form of infrastructural augmentation, incrementally reshaping how humans interact with knowledge, work, and each other. Their integration, if guided by inclusive and ethical principles, can contribute to the ongoing evolution of sociotechnical systems toward greater complexity, reflexivity, and resilience.

Yet this optimistic narrative sits in productive tension with Dan Hendryckx's cautionary framing, which applies Darwinian logic directly to AI model development itself. Hendrycks argues that, as in biological ecosystems, only the most "fit" models survive competitive pressure, potentially privileging capabilities (e.g., scale, speed, or strategic manipulation) that run counter to human values and societal well-being [30]. In this view, selection dynamics may inadvertently reward undesirable behaviors or misalignments unless governance and alignment strategies ensure that "fitness" aligns with ethical and human-centered criteria.

6. COUNTERARGUMENTS AND REBUTTALS

Critiques from Livingstone [2] and Walsh [3] argue that LLMs risk entrenching epistemic biases, exacerbating misinformation, and displacing human creativity under the guise of augmentation. While these concerns are valid, they overlook the dynamic and regulatory nature of system adaptation. LLMs are not final products but evolving tools embedded in sociotechnical ecosystems. Their integration depends on institutional reflexivity,[19] iterative governance, and ethical boundary-setting, as emphasized by the Cambridge Handbook of AI [24]. When these conditions are met, LLMs become facilitators of distributed agency rather than instruments of disempowerment.

Cowin [31] adds a cautionary note by likening the rise of autonomous AI agents to mythical awakenings, the "Kraken Wakes."[20] While evocative, such metaphors risk obscuring human responsibility and oversight. LLMs lack agency in the ontological sense; they function within parameters set by human design, intent, and contextual deployment. Thus, rather than fueling speculative anxiety, efforts should focus on steering AI integration through a lens of ethical resilience and sociotechnical balance.

6.1. Counterargument: LLMs Disrupt Employment and Knowledge Structures

- **Critics' Claim:** LLMs jeopardize employment by automating cognitively complex tasks and diminishing the role of human expertise in knowledge production.
- **Rebuttal:** Technological transitions have historically led to job displacement *and* the emergence of new

[19] **Institutional Reflexivity:** The capacity of an institution to examine and adapt its own structures, assumptions, and feedback mechanisms.

[20] **Kraken Wakes:** In the novel, deep-sea creatures surface unexpectedly to wreak havoc. This metaphor is extended to describe latent, emergent disruptions in higher education.

professional domains. Rather than wholesale replacement, what unfolds is a redefinition of roles. LLMs are likely to redistribute cognitive labor, prompting reskilling and hybrid collaboration models in which human creativity and AI complement one another. The resulting equilibrium will reflect a recalibrated rather than diminished epistemic and economic structure.

6.2. Counterargument: LLMs Represent a Technological Revolution

- **Critics' Claim:** The rapid development, diffusion, and adoption of LLMs signify a revolutionary break from previous technological paradigms.
- **Rebuttal:** While the velocity of adoption is notable, it does not alone constitute a revolution in the Kuhnian sense [32]. Revolutions imply structural paradigm shifts and systemic ruptures. LLMs, by contrast, enhance existing infrastructures in language processing, communication, and knowledge work. They extend and refine prior innovations, suggesting an evolutionary trajectory marked by recursive integration and adaptive transformation rather than abrupt epistemic overhaul.

7. DISCUSSION AND IMPLICATIONS

Having examined the core concepts, definitions, tensions, and counterarguments surrounding Large Language Models (LLMs) in higher education, we now return to the two guiding questions posed at the outset. This section explores them in full, drawing together the paper's key findings and positioning them within broader institutional, pedagogical, and epistemological contexts. The aim is to synthesize insights and articulate concrete implications for future practice, policy, and research in the age of Generative AI.

Q1: How do we balance innovation with accountability?

Balancing innovation with accountability in the development and deployment of Generative AI (GenAI) and Large Language Models (LLMs) requires a systems-level approach that integrates ethical foresight, dynamic regulation, and institutional reflexivity. Innovation must be accompanied by governance frameworks that evolve in tandem with technological capabilities. These include principles of transparency, explainability, fairness, and human oversight, ensuring that LLMs serve as augmentative tools rather than autonomous agents.

Effective accountability begins with *feedback-responsive regulation*, where LLMs are continuously evaluated through real-time auditing, risk-based classification, and red-teaming to identify vulnerabilities before deployment. Such mechanisms allow institutions to adjust policies proportionally, fostering experimentation in low-risk areas while safeguarding domains [33], [34].

Accountability also depends on a participatory infrastructure. Governments, universities, developers, and the public must co-construct norms and standards that reflect shared values. As the UNESCO Recommendation [26] on the Ethics of Artificial Intelligence [35] emphasized that principles such as proportionality, non-maleficence, and human determination should guide both innovation and restraint..

Ultimately, the challenge is not to slow innovation, but to steer it responsibly. Institutions must evolve toward *adaptive regulatory ecosystems* capable of absorbing technological novelty without sacrificing trust, equity, or epistemic integrity.

Q2: How do we reconcile the divergent goals of business and education in AI adoption?

Reconciling the divergent goals of business and education in the adoption of Generative AI (GenAI) and Large Language Models (LLMs) requires recognizing that both traditions, vocational pragmatism and classical liberal education, stem from foundational tensions in American intellectual history [36]. Benjamin Franklin emphasized utilitarian training for economic participation, while Thomas Jefferson envisioned education as a means to cultivate enlightened, civically engaged citizens. This dialectic has persisted across centuries, reemerging in the form of competing educational ideologies such as Dewey's progressive, student-centered pedagogy versus Thorndike's behaviorist, efficiency-driven model, an enduring tension well documented by Kliebard in *The Struggle for the American Curriculum, 1893–1958* [37].

Today, this historical struggle finds new expression in the differing logics of business and education [38], [39]. While businesses prioritize innovation, efficiency, and competitive advantage, education is tasked with fostering ethical reasoning, epistemic humility, and democratic agency. The risk is not merely practical, but epistemological. GenAI answers questions but does not pose new ones; it recombines existing knowledge but does not originate novel paradigms. If educational institutions emulate business logic without reflection, they risk eroding the foundational conditions that make inquiry and original thought possible [40].

A systems-level reconciliation must involve mutual adaptation. Educational institutions should redesign curricula to integrate AI literacy alongside enduring human capacities, creativity, interpretation, ethical judgment, and reflexivity. Concurrently, businesses must invest in responsible AI governance, human-centered design, and lifelong learning initiatives that recognize the distinct role of education in shaping citizens, not just workers. Cross-sector collaborations, such as shared AI literacy frameworks, joint advisory boards, and research-practice partnerships, can serve as infrastructural bridges between these domains [41].

Ultimately, reconciliation does not imply homogenization. It demands a choreographed interdependence that allows AI to enhance pragmatic capabilities while preserving the ontological depth and transformative potential of education, a balance essential for long-term societal flourishing.

Ultimately, reconciliation does not imply homogenization. It requires a choreographed interdependence that enables AI to enhance functional capabilities while preserving the ontological depth and transformative potential of education—a balance essential for long-term societal flourishing.

8. CONCLUSION

While the capabilities of Large Language Models (LLMs) are undeniably transformative, this paper has argued that their integration reflects an evolutionary, not revolutionary, shift in the sociotechnical landscape of higher education. LLMs amplify existing institutional tensions rather than overturn paradigms, revealing the fragility of traditional assumptions about authorship, assessment, and cognitive labor.

Rather than resisting these changes, educational systems must engage in adaptive regulation, guided by principles of cybernetic governance[21] and Homeostasis. The future of LLM integration lies not in containment but in the strategic cultivation of feedback-responsive ecosystems, where human agency, ethical oversight, and inclusive participation are preserved amid machine-augmented productivity.

A central question emerging from this transition is how to assess authentic understanding when machines can simulate it so convincingly. The answer lies in shifting from static evaluations of output to dynamic assessments of process, intentionality, and epistemic agency. Authentic understanding is demonstrated not through linguistic polish alone, but through engagement, contextual reasoning, and transparent thought development over time. Institutions must therefore prioritize dialogic assessments, metacognitive artifacts[22], and scaffolded tasks that foreground human judgment and ethical discernment within augmented environments.

Ultimately, LLMs are not autonomous disruptors, but instead technologies whose influence is shaped by the values, policies, and epistemic commitments of the systems that adopt them. Their role in education will be determined not by their technical power alone, but by the institutional capacity to evolve, deliberately, reflexively, and equitably.

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[i] Here, "epistemological and technological change" refers to the dual transformation of higher education in response to artificial intelligence. On one hand, it entails a reconceptualization of knowledge production and authorship in an environment where generative AI challenges

traditional notions of originality and human agency. On the other, it implicates the rapid evolution of digital tools and platforms that outpace existing pedagogical frameworks.

[ii] The choices made during model development (training data selection, architectural design) and deployment (integration context, safeguards) are equally consequential and rooted in human intention. Highlighting these dimensions would round out the discussion of responsibility and better reflect the full lifecycle of LLM influence. Due to the scope of the paper, further discussion of this idea will have to be explored in future publications.

[iii] While the concept of homeostasis originated in biology, it was later adopted and elaborated by cybernetics to describe regulation and feedback in mechanical, computational, and social systems.