Measuring Entanglement: The Entagogy Framework for Bloom-Level Adaptivity in AI Learning System

Alexander Harris[1], Stephanie Holt[2]
Belgravia Education[1]
Brunel University[2]
UK

Abstract

This paper advances Entagogy as a necessary systems-theoretical framework and build specification for designing human–AI learning systems that learn the learner. Grounded in Luhmannian structural coupling and an entangled reading of Vygotsky's ZPD (e-ZPD), Entagogy formalises the interaction between the Human Cognitive System (HCS) and an AI Semantic Subsystem (AISS) as a closed control loop. Treating Bloom's "two-sigma" effect as an engineering brief, we outline measurement plans and acceptance criteria that render the framework falsifiable and testable across contexts. The article establishes Entagogy's scope and boundaries, distinguishes it from adjacent lenses (e.g., entangled pedagogy, generic learning analytics), and offers concrete artefacts—state-machine diagrams, threshold tables, and governance checks—to support replication, evaluation, and responsible scaling. Crucially, we argue that existing educational frameworks: pedagogy, andragogy, heutagogy, cannot be simply transposed onto AI-led learning systems without distortion. Each addresses particular human/AI contexts of teaching and learning, yet none accounts for the autopoietic co-construction that arises when human cognition is structurally coupled with algorithmic subsystems. Research that fails to differentiate which framework is operative risks producing false outcomes, misattributing effects, and obscuring the very mechanisms that drive adaptivity. By advancing Entagogy, we seek to provide a coherent theoretical foundation for future inquiry, one capable of supporting both rigorous scholarship and the responsible development of Intelligent Learning Machines.

1. Introduction

Bloom's seminal claim that one-to-one tutoring yields learning gains two standard deviations above conventional instruction has become a benchmark for educational innovation. Recent advances in Intelligent Tutoring Systems (ITS), particularly those powered by large language models and adaptive tutoring platforms, have reignited efforts to close the '2 Sigma Gap.' Yet research in this field is hindered by two persistent problems.

First, many studies continue to misclassify learning frameworks, conflating pedagogy, andragogy, and heutagogy with the chronological age of the learner. This simplification obscures the role of autonomy, metacognitive readiness, and self-direction in shaping outcomes, thereby producing misleading attributions of system efficacy.

Second, claims of adaptivity in AI systems are often overstated. Many platforms function responsively, adjusting content in pre-determined ways, without demonstrating the structural coupling or bidirectional feedback characteristic of genuinely adaptive tutoring. Such conflation risks inflating effect sizes and obscures the design conditions necessary to approach Bloom-level gains.

Together, these issues constrain both empirical research and practical development. Without a diagnostic framework to distinguish responsive from adaptive ITS, and without clarity on how frameworks of learning are applied, the field risks generating results that cannot be meaningfully compared or replicated.

This paper introduces Entagogy, a systems-theoretical framework that reconceives AI-mediated learning as a process of autopoietic co-construction. Drawing on Luhmann's approach to structural coupling, Entagogy defines learning as an entangled relationship in which the AI learns the learner while the learner learns the subject. In this formulation, an entangled Zone of Proximal Development (e-ZPD) emerges as the diagnostic threshold for genuine adaptivity.

By operationalizing criteria such as real-time learner-model updates, sustained interactional rhythm, governance permeability, and the presence of exogenous perturbations to prevent autopoietic drift, this paper offers a structured framework for distinguishing between merely responsive and genuinely adaptive AI learning models. This diagnostic clarity ensures that research outcomes can be validly interpreted and compared, as well as providing developers with concrete benchmarks for design.

This paper therefore positions Entagogy not only as a conceptual advance but also as a practical tool for

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benchmarking ITS' against Bloom's 2 Sigma challenge. In doing so, it addresses the methodological weaknesses that currently constrain empirical research and supports the development of adaptive platforms capable of sustaining the conditions for transformative learning gains.

2. Empirical Landscape

Bloom's seminal claim that one-to-one tutoring can yield learning gains of two standard deviations above conventional instruction established a benchmark that continues to shape educational innovation [1]. Decades of subsequent research, however, show that while both human and intelligent tutoring systems are highly effective, they rarely exceed gains of around 0.8σ.

A recent systematic review consolidates this evidence, drawing together meta-analyses, controlled trials, design-based experiments, and evaluation frameworks. It shows that AI-powered tutors, including large language model systems, often outperform traditional or even active-learning classrooms, delivering meaningful improvements in engagement, efficiency, and measured outcomes. Yet the gains remain uneven: promising in medical and professional education, positive but modest in K–12 classrooms, and variable across higher education. The review also stresses that what is frequently described as "adaptive" tutoring is often better characterised as responsive branching, with few systems demonstrating real-time bidirectional adjustment or sustained dialogic rhythm [2].

The synthesis identifies recurring methodological limitations. Many interventions are extremely short in duration, creating the risk of novelty effects, and studies often conflate pedagogy, andragogy, and heutagogy with learner age rather than examining autonomy or metacognitive readiness. Evidence also suggests differentiated impacts, with middle school students benefitting more consistently than older learners, and with results concentrated in STEM domains and in US/Asian contexts. Across these cases, the review isolates personalisation, adaptivity, and immediate feedback as the three most reliable drivers of positive outcomes, especially when combined with teacher collaboration and opportunities for self-regulation and mastery learning.

Perhaps most strikingly, none of the reviewed studies addressed ethical concerns such as fairness, transparency, or accountability. This omission underscores the field's current blind spots. However, taken together, the evidence suggests that AI tutors can now rival the effectiveness of skilled human tutors under specific conditions. Nevertheless, consistent breakthroughs beyond the well-documented plateau remain elusive. Progress will depend on clearer definitions of adaptivity, attention to ethics, and diagnostic standards capable of distinguishing genuine entanglement from surface-level responsiveness [2].

3. Discussion: Introducing Entagogy

Contemporary literature demonstrates the promise of AI-powered personalised learning, yet it also reveals persistent conceptual and methodological weaknesses. Without a shared diagnostic, studies risk conflating responsiveness with adaptivity, overstating system effects and under-specifying the conditions in which they occur. Equally, the widespread reduction of pedagogy, andragogy, and heutagogy to age categories obscures the role of autonomy, metacognitive readiness, and learner agency. These weaknesses generate two consequences: research findings are often difficult to compare across contexts, and intelligent tutoring systems (ITS) are built without clarity on the structural features that underpin lasting learning gains.

A new framework is therefore required to bridge these gaps. For research, such a framework must offer a diagnostic lens that allows outcomes to be interpreted in terms of genuine adaptivity rather than surface-level responsiveness. This enables effect sizes to be contextualised against system properties rather than demographic proxies, reducing the risk of false positives.

For development, the framework must specify measurable criteria that can be engineered into AI learning models, creating a pathway for benchmarking prototypes and iteratively refining them against Bloom's challenge.

3.1. Entangled Learning and the Case for a Luhmannian View

The contemporary shift toward AI-mediated learning requires more than descriptive accounts of interaction between humans and machines. Existing theoretical frames have provided important openings. Latour's Actor–Network Theory collapses the human–machine divide by treating artefacts and people as equally agential nodes [3] and Postdigital scholars emphasise that these networks are already political, shaped by code, infrastructures, and business models that contour participation [4]. Posthumanist approaches extend this critique by arguing that knowledge itself emerges through material-discursive entanglements rather than circulating through neutral pipelines [5], [6].

Yet description alone is insufficient. In Luhmann's systems theory humans and technologies are operationally closed but structurally coupled,

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exchanging 'irritations' that allow adaptation while preserving their distinct logics [7]. Education itself can be understood as a self-producing communication system, one that remains viable by coupling with its environment. Here, learners and AI subsystems continuously exchange signals with perturbations from the outside world creating an ecology for learning that moves beyond simple coupling. Adaptive tutoring illustrates this reciprocity: models recalibrate in response to learner performance and affect, while institutions adjust practices and policies in response to AI-mediated shifts.

3.2. Epistemological Framework of Entagogy

Entagogy is grounded in an onto-epistemological position that treats knowledge as relational, co-constructed, and emergent through the continual intra-actions of human and non-human agents. Drawing on Barad's notion of agential cuts [5], it recognises that distinctions such as learner and AI, knowledge and context, are not pre-given but enacted and reconfigured through interaction. Within this view, epistemology is not static but continually renegotiated inside learning ecologies.

At the centre of this framework lies the principle of distribution agency. Rather than privileging either the learner or the AI as the sole locus of autonomy, Entagogy situates learning within the adaptive interplay of structurally coupled human cognitive systems (HCS) and AI semantic subsystems (AISS). This coupling occurs within the entangled Zone of Proximal Development (e-ZPD), a dynamic space in which human capacities for cognition, affect, and strategy are co-constituted with the adaptive functionalities of the AI system (see Figure 1).

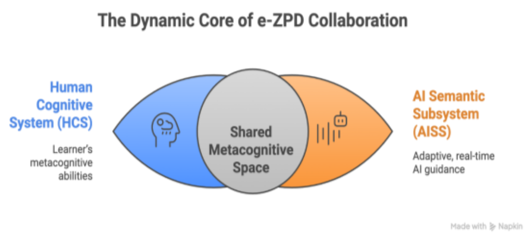

Figure 1. Zone of Proximal Development (ZPD)

Knowledge production is therefore redefined. It is no longer understood as linear transfer or acquisition but as an iterative, recursive process emerging from the reciprocal perturbations and irritations between human and machine [8], [2]. Each exchange produces new conditions for the next, so meanings and understandings evolve through continual co-adaptation. To evaluate such processes, Entagogy calls for robust criteria of knowledge validation: internal coherence within the system, recursive reflexivity across learner and AI interactions, and ethical responsiveness to the broader ecology. Methods must therefore be sensitive to systemic adjustments and capable of tracking co-evolutionary dynamics between learner activity and AI-driven analytics.

Responsible innovation also becomes intrinsic to the framework, ensuring that knowledge claims are not only empirically robust but also socially accountable [9]. In this way, Entagogy situates epistemology and ethics as mutually reinforcing: learning is validated not simply by outcomes, but by the integrity, fairness, and inclusivity of the processes that generate them.

Postdigital scholarship reminds us that HCS/AISS couplings are already political, shaped by infrastructures, business models, and code [4]. Posthumanist theory presses further, locating knowledge within material–discursive entanglements [5], [6]. Luhmann's systems theory adds the essential language of autopoiesis, showing how human and technological systems remain distinct yet adapt through structural coupling [7].

Yet none of these approaches alone resolves the empirical and methodological challenges of AI-mediated learning. ANT and posthumanism describe symmetry and entanglement but lack criteria for persistence. Luhmann explains coupling but remains abstract, without guidance for diagnosis or design. The consequence is that both research and development risk misclassifying responsiveness as adaptivity, overstating outcomes while under-specifying the conditions required for Bloom-level gains.

3.3. Coupling Human Psychology and ITS Led Learning

Vygotsky's Zone of Proximal Development (ZPD) adds to this discourse through the lens of educational psychology: a learner advances by working with a more knowledgeable other across a span of development that cannot be reached alone [10]. Yet, as Table 1 makes clear, the ZPD in its classical form is insufficient for the realities of AI-rich learning.

The standard ZPD assumes a fixed source of expertise, a relatively stable span of development, and one-directional scaffolding mediated primarily through language. These assumptions collapse in an environment where human and artificial systems are structurally coupled. In such settings, expertise is situational, guidance is polycentric, and mediation extends beyond speech into multimodal and algorithmic cues [8]. The source of expertise is no longer stable but dynamically shared; the zone is not bounded once but redrawn continuously; and

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scaffolding becomes mutual, with learner actions shaping the AI model while the AI's adjustments reshape learner strategy.

It is for this reason that Entagogy advances the concept of the entangled ZPD (e-ZPD). Unlike a general Luhmannian approach, which offers a broad theory of systems and communication, the e-ZPD provides a usable map for both researchers and designers. It reframes personalisation as structural coupling rather than content adjustment, showing where expertise resides at any moment, how mediation unfolds across multimodal channels, and under what technical conditions (adaptivity, low latency, permeable governance etc.) the coupling sustains itself.

Table 1. ZPD / e-ZPD

Dimension	Classic ZPD (Vygotsky)	e-ZPD (Entagogy)
Mediation	Human "more knowledgeable other" (teacher, peer) provides scaffolding and feedback	Mediation occurs through both human and AI; feedback and support are multimodal, adaptive, and algorithmically mediated
Guidance	Largely unidirectional (teacher/peer guides learner)	Guidance is bidirectional and dynamic; both learner and AI can act as "more knowledgeable other" at different moments
Stability	Zone shifts as learner develops, but structure is relatively stable within an interaction	Zone is fluid, shifting moment to moment in response to both learner and AI adaptation; the boundary is co-constructed
Agency	Primarily human, with teacher/peer as agent of change	Distributed and non-hierarchical; agency is shared, negotiated, and emergent from HCS–AISS coupling
Boundary	Defined by human social, cultural, and cognitive context	Boundary includes technical, algorithmic, infrastructural, and exogenous (social, policy, technical) influences
Reciprocal Learning	Implicit—teacher may learn about the learner, but focus is on learner's development	Explicit—AI and human both adapt and "learn"; each system updates its model in real time
Mode of Feedback	Verbal, social, contextual, often slow	Multimodal: text, speech, visuals, haptic; can be near-instantaneous and deeply personalised

The diagnostic value is twofold. For researchers, the e-ZPD clarifies what counts as genuine adaptivity: rapid role transfers, structural reciprocity, and continuously shifting boundaries. Without this lens, studies risk misclassifying responsiveness as adaptivity, producing false positives in effect size claims. For developers and psychologists, the e-ZPD defines measurable prerequisites for Bloom-level gains.

In sum, Entagogy's use of the e-ZPD is not a theoretical embellishment but a practical necessity. Where classical ZPD cannot account for the dynamics of AI-augmented learning, and where Luhmann alone remains too abstract, the e-ZPD provides the conceptual and diagnostic bridge. It couples human psychology with machine learning in a way that makes Bloom's challenge not only intelligible but testable.

4. Limitations of Entagogy

While Entagogy provides a powerful and versatile theoretical lens to examine how entanglement between an AISS and HCS reciprocally shape learning, it is crucial to acknowledge that not every interaction between learner and AISS constitutes entagogic learning. The framework explicitly demands certain structural conditions to be fulfilled before the desired recursive, co-constructive coupling emerges. In other words, simply deploying an advanced AI tool or interacting frequently with an adaptive learning environment does not automatically yield entagogic outcomes (see Table 2).

Table 2. Required conditions of Entagogy

Dimension	Why it matters for Entagogy	Typical failure signal
Context & Infrastructure	Reliable bandwidth, up-to-date devices and teacher training are prerequisites for low-latency adaptivity.	Technical "hiccups" force the AI to drop into fallback modes, re-humanising the session.
Data Ethics & Privacy	Continuous modelling relies on granular trace data; privacy regimes (COPPA, GDPR) can throttle that flow.	Learners encounter generic feedback because fine-grained logs are masked or siloed.
Bias & Cultural Fit	An AISS tuned on majority-culture discourse may mis-frame language, gesture or prior knowledge.	Minority learners receive irrelevant or pathologising prompts, undermining psychological safety.
Interpretability & Trust	Black-box adaptivity can provoke teacher or learner scepticism, stalling the recursive loop.	Users override or ignore AI advice, reverting to pre-AI routines.
Domain Boundaries	Some competencies (e.g. tacit craft skills, embodied movement) exceed current NLP-centric AISS capacities.	Progress plateaus despite high adaptivity scores, signalling that the target skill needs physical co-presence.
Scaling Effects	What couples well in a pilot may overload compute budgets or moderation capacity at district scale.	Latency climbs and governance locks tighten, collapsing the coupling.

Central to the Entagogy framework is the notion that meaningful learning arises from the dynamic interplay, or structural coupling, between the Human Cognitive System (HCS) and the AISS [11]. This interplay, however, can only flourish when specific enabling thresholds are consistently maintained. Without satisfying these critical thresholds - adaptivity, latency responsiveness, and governance permeability - the interaction between learner and AISS reverts from a truly co-evolving partnership into a more traditional, unilateral dynamic. Recognising these limits is essential not only for accurately diagnosing when and why entagogic approaches may falter, but also for refining the design of AI-mediated environments to better meet these foundational conditions

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4.1. Conditional Coupling

Autopoietic coupling between the Human Cognitive System (HCS) and the AISS constitutes the foundational mechanism of the e-ZPD. However, such coupling is neither automatic nor guaranteed. It depends critically on three enabling thresholds, each of which must be met to sustain a genuinely recursive, co-constructive learning ecology. These thresholds: adaptivity, latency, and governance permeability, define the structural conditions under which learner and AISS can operate as distinct yet mutually responsive systems. Where any one threshold fails, the system reverts to a default mode: either a traditionally human-led scaffold or a heutagogy building AI tutor.

Adaptivity: For autopoietic coupling to take hold, the AISS must operate not as a static feedback engine but as a live epistemic partner [8]. This requires that the system continuously update its internal learner models within the same session, recalibrating predictions, scaffolds, and interface strategies based on ongoing learner inputs; be they cognitive (e.g., answer correctness), behavioural (e.g., pacing), or affective (e.g., sentiment shifts).

If the system's adaptivity is too coarse-grained (e.g., relying on pre-scripted branching paths) or updates only at the end of a session, the illusion of co-construction collapses. The learner ceases to perceive the AISS as a responsive partner and instead experiences it as a static tutor; one that repeats, rather than evolves. This breaks the recursive loop and inhibits the formation of structural coupling. As a result, the ZPD becomes frozen, linear, and teacher-dependent once again.

Latency: The temporal rhythm of feedback is equally critical. For coupling to feel and be dialogic, the system must respond fast enough to maintain the attentional envelope. Research suggests that this window, particularly for visual and interactive tasks, falls within a 300–600 millisecond range.

When the AISS responds too slowly it breaks the interaction's epistemic rhythm. The learner begins to reassert control and autopoiesis is broken. In effect, the AI is demoted from partner to passive tool. Conversely when feedback is instantaneous and semantically relevant, the AISS becomes experienced as an active participant, capable of "thinking with" the learner in real time. This speed-based alignment is essential for establishing the recursive irritations that define autopoietic systems.

Governance permeability: Governance must ensure ethical safety without sterilising the system's responsiveness through programmable transparency, not hard-coded stasis [9]. The capacity of an AISS depends on institutional policy architecture that either permits or prohibit algorithmic reparameterisation. Where audit rules, compliance frameworks, or locked-down governance APIs prevent the system from adapting (for example, in the name of fairness audits or GDPR compliance) the AISS becomes inflexible. It can still recommend, but it cannot learn.

This results in what we might call pseudo-coupling: the learner continues interacting, but the system is no longer responding in kind. The feedback becomes performative, not generative. Worse still, over time the system may default to protecting itself from liability rather than optimising learning outcomes. A rigidly governed AISS risks functioning more like a grading assistant than a cognitive partner.

4.2. Regressive Outcomes in the Absence of Coupling

The integrity of the entangled Zone of Proximal Development (e-ZPD) is contingent upon the simultaneous fulfilment of three structural conditions: adaptivity, latency responsiveness, and governance permeability. Where any of these conditions is absent or compromised, the autopoietic coupling between the Human Cognitive System (HCS) and the AI Semantic Subsystem (AISS) is disrupted. In such instances, the recursive perturbations and mutual irritations that sustain co-evolution between subsystems are severed, resulting in a reversion to more traditional, linear instructional dynamics. Specifically, the breakdown of each threshold yields distinct regressions:

In the absence of adaptivity, the AISS reverts to pre-scripted instructional patterns. Rather than responding in real time to learner inputs, the system defaults to static, pre-determined sequences. This collapse into a didactic feedback loop inhibits the co-construction of meaning and re-establishes the educator or system as a unilateral source of knowledge.

When latency exceeds the learner's attentional threshold, the illusion of dialogue is broken. Delays in system feedback diminish the perceived responsiveness of the AI, prompting the learner to disengage from co-constructive exchange. In such scenarios, learners are likely to revert to self-scaffolding strategies, effectively reclaiming full agency and undermining the dialogic reciprocity that characterises an entangled ZPD.

If governance frameworks restrict algorithmic re-parameterisation, the AISS is rendered operationally inert [9]. Policy constraints that prevent the system from adapting its internal models in response to emergent learner behaviour result in a rigid and prescriptive interaction. The learner, in turn, is forced to adapt their learning strategies around the fixed constraints of the tool, effectively transforming the AISS from a cognitive partner into a static recommender system.

In each of these cases, the ZPD regresses to a conventional scaffolding paradigm: either a human-led model in which the educator assumes sole responsibility for guidance, or a system-led routine in which the AI dictates fixed pathways without co-adaptive responsiveness. In either instance, the defining characteristic of Entagogy; the recursive, co-autopoietic interaction between learner and intelligent system, is suspended.

4.3. Autopoietic Drift and the Necessity of Exogenous Irritation

Autopoietic systems reproduce their own operations; without perturbation they drift into reductive self-confirmation [7]. To avoid siloed echo-loops, Entagogy hard-wires mandatory irritations from neighbouring function systems (see Table 3). These loops stabilise the learning ecology without breaching operational closure: each subsystem retains its code (e.g., cognitive validation, policy compliance) while remaining sensitive to perturbations.

Table 3. Exogenous Irritations in Entagogy

External system	Irritation channel	Typical cadence	Example signal	Resulting adjustment
Institutional policy	Governance API call-outs	Daily cron or event-trigger	"Equity disparity > 10 %"	AI re-balances content difficulty, teacher receives alert (Steiner-Khamsi, 2021)
Peer community	Social annotation layer	Real-time	High divergence in peer answers	AI injects peer exemplar, learner invited to critique
Cultural knowledge base	Live corpus sync	Weekly	New taxonomy term enters discipline	Suggestion engine surfaces updated concept map
Ethical oversight	Bias-audit webhook	Monthly or ad hoc	Fairness test p-value < .05	Model weights recalibrated, bias notice displayed (Rosiek et al., 2024)

5. Approaches to Methodology in Entagogic Research

Both researchers and developers must be able to determine when entagogy is occurring as distinct from pedagogy, andragogy, or heutagogy. Without diagnostic clarity, studies risk both misclassifying learning effects and misleading the development of intelligent tutoring systems.

Entagogy therefore advances not only a theoretical framework but also a research orientation. Rooted in systems theory, it supplies the criteria for recognising the formation of an entangled Zone of Proximal Development (e-ZPD), in which a human cognitive system (HCS) and an AI semantic subsystem (AISS) become structurally coupled [7]. The methodological focus thus shifts from aggregate learning outcomes to the identification of real-time conditions under which entanglement occurs, stabilises, or fails. This requires an inquiry architecture that can track emergent knowledge across cognitive, technical, and socio-material layers.

5.1. The Four Lenses of Entagogy

Rather than prescribing a single protocol, Entagogy proposes a transdisciplinary research stance that is sensitive to three commitments. First, to structural coupling, ensuring that analysis remains centred on reciprocal adaptation rather than unilateral instruction. Second, to reciprocal metacognition, attending to the ways learner strategies and AI feedback co-constitute one another over time. Third, to ethical reflexivity, embedding concerns of bias, equity, and inclusion within the very criteria used to recognise entanglement [11]. These commitments establish the foundation for a plural yet coherent methodological toolkit (see Figure 2).

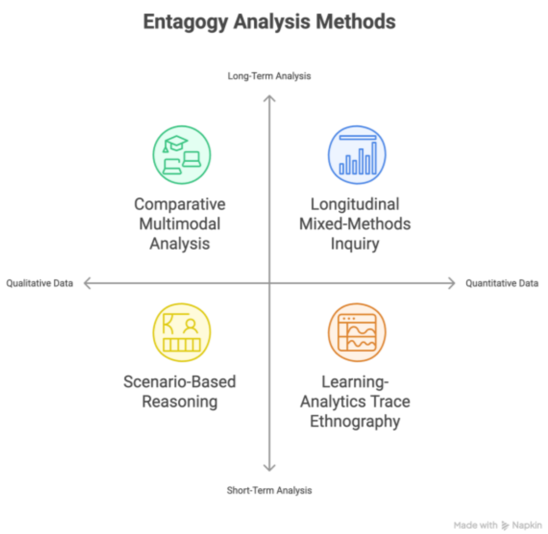

Figure 2. Research Methodology for Entagogy

It is important to note that learning is conceived as a co-autopoietic process in which human cognition and AI semantic subsystems continuously perturb and recreate one another, research designs must operate across scales. Micro-level loops of interaction must be mapped alongside macro-level stabilisations such as curricular adjustments or institutional policy shifts. To achieve this, Entagogy advances a recursive research architecture organised around four complementary lenses.

Scenario-based reasoning functions as the imaginative front-end of entagogic research. Using design fictions, participatory studios, or agent-based simulations, researchers can model hypothetical learning ecologies, surfacing latent variables, ethical inflection points, and threshold conditions such as adaptivity, latency, and governance permeability [11]. Each scenario serves as a stress-test, perturbing the not-yet-built system so that potential couplings and breakdowns are revealed before deployment.

Learning-analytics trace ethnography then examines entagogy at the level of practice. Clickstreams, gaze paths, conversational turns, and affective signals are read simultaneously as quantitative traces and as cultural artefacts [8]. Algorithmic pattern-recognition highlights candidate moments of bidirectional metacognition, while ethnographic annotation situates these events within learners' lived experience. Through this lens, quantitative measures and qualitative narratives inter-animate each other to expose how micro-irritations cascade into meso-level trajectories.

Longitudinal mixed-methods inquiry provides the temporal depth required to establish whether Entagogy has occurred. Repeated measures of cognitive–affective alignment, policy–pedagogy coupling coefficients, and learner-authored reflections reveal how early perturbations consolidate into stable routines or drift into over- or under-coupling. Interviews and classroom observations ground these quantitative patterns in context, ensuring that analysis captures both structural stability and human experience.

Finally, comparative multimodal analysis supplies the lateral perspective needed for generalisation. By aligning discourse analysis, interface semiotics, and biometric or affective data across multiple sites, researchers can separate universal signatures of entagogic coupling from local adaptations. Cross-case synthesis prevents over-reliance on any single implementation and anchors theory-building in diverse empirical bases.

5.1.2. Recursive Research Architecture. These four lenses are not sequential stages but interlocking components of a recursive research loop. Insights from speculative scenarios recalibrate trace-analytic parameters; emerging ethnographic patterns shape longitudinal designs; cross-case syntheses feed back into the next wave of scenario-building. In this way, the methodological apparatus mirrors Entagogy itself: a dynamic system that learns by continuously perturbing and refining its own operations.

The recursive architecture allows scholars to establish not only whether Entagogy has taken place but also how it stabilises, transforms, or fails. By embedding ethical and equity commitments - psychological safety, inclusion, transparency - at the core of each analytic move, the approach ensures that methodological rigour is inseparable from responsibility.

6. Creating A Diagnostic Protocol for Entagogy

Without a protocol that turns Entagogy's thresholds (adaptivity, guidance rhythm/latency, governance permeability, reciprocity, perturbation, equity) into testable invariants, development teams risk shipping responsive systems that only mimic adaptivity or over-fitting to short-run gains that do not persist. The Diagnostic Protocol formalises those invariants and aligns them with the four research lenses so results are auditable and comparable across deployments enabling both researchers and developers to accurately gauge when genuine entanglement is occurring, rather than when a system merely looks personalised.

6.1. Integrating a synergy metric to detect entanglement

To operationalise 'when' entagogy occurs this paper integrates findings from Riedl and Weidmann [12]. Introducing a Bayesian Item Response Theory framework that decomposes performance into individual ability (θ) and collaborative ability (κ), validated on interactive human–AI data; critically, κ is distinct from θ and varies with user factors (e.g., perspective-taking), Riedl and Weidmann provide uncertainty estimates and model comparisons. Their analysis shows substantial human–AI gains and clear differences between AI models (e.g., higher synergy with GPT-4o than Llama-3.1-8B), while demonstrating that collaborative ability can be estimated separately from solo ability. This offers a principled, model-agnostic signal for when synergy/entanglement is present.

We therefore treat $\kappa > \theta$ (beyond a pre-registered margin and with credible intervals) as a necessary *statistical* indicator that must co-occur with structural indicators from Entagogy (within-session adaptivity and role-transfer reciprocity, sub-second guidance rhythm, governance permeability, and stability under exogenous perturbation). This binds outcome-level synergy to the e-ZPD's system properties, preventing false positives from answer-revealing or latency-masked boosts.

6.2. Study-level Operationalisation

At the study level, entanglement can therefore be identified by alternating solo and assisted trials on calibrated or near-isomorphic items so that performance can be decomposed into individual ability (θ) and collaborative ability (κ).

The trial schedule should be randomised and sparse enough to avoid practice artefacts while providing sufficient information for Bayesian estimation. Prior to data collection, the entanglement decision rule must be pre-registered—for example, $\kappa - \theta > \delta$ with a 95% credible interval (CrI) and concurrent satisfaction of structural thresholds (within-session adaptivity, sub-second guidance rhythm, evidence of role-transfer reciprocity, and compliant governance). This aligns the outcome signal (κ exceeding θ) with the system properties that Entagogy treats as necessary for an e-ZPD to exist.

Validation ensures that observed κ gains reflect co-construction rather than content leakage or answer-revealing. To this end, learning-analytics can be paired with trace ethnography: dialogic turns tagged for reciprocity (two-way metacognitive prompts, plan–monitor–evaluate moves) and micro handovers (AI↔learner shifts in guidance). These qualitative tags can then be time-locked to the quantitative traces so that κ elevations can be attributed to reciprocal adaptation rather than superficial assistance.

Durability is assessed longitudinally with researchers tracking whether κ is sustained or increasing while hint reliance declines, indicating entanglement without dependency. Robustness can be probed through exogenous irritations (policy or content updates, teacher interventions, or interface changes) and by examining whether κ and the structural thresholds remain stable under these perturbations.

Equity can further be gauged when κ estimates are disaggregated by subgroup (e.g., language background, gender, connectivity context), with pre-specified margins defining unacceptable gaps and documented corrective actions when thresholds are exceeded. The diagnostic protocol therefore has the potential to embed ethical responsiveness within the same evidentiary framework used to claim entanglement.

Finally, Scenario-based reasoning is able to provide stress-tests as to whether design conditions are sufficient for κ to emerge; trace ethnography instruments latency distributions and role-transfer events that substantiate reciprocity; longitudinal panels test the persistence of κ and structural thresholds under perturbations; and comparative multimodal analyses examine the generalisability of entanglement across domains, infrastructures, and cohorts. Together, these lenses turn the protocol into a recursive apparatus capable of determining when an e-ZPD has formed and whether it is maintained.

6.3. Reporting standardisation

For replication and meta-analysis, studies should report:

(1) The **$\kappa - \theta$** estimates with credible intervals and the pre-registered entanglement rule.

(2) Latency statistics (median, P95) and latency-breakdown correlations.

(3) Counts of within-session learner-model updates and scaffold revisions.

(4) Reciprocity markers (AI↔learner role-transfers; two-way metacognitive prompts/responses).

(5) Enacted governance changes/self-tuning bounds.

(6) Equity-disaggregated κ and remediation.

(7) The log of exogenous irritations and system adjustments.

6.4. Implementation (recursive apparatus)

The Diagnostic Protocol is recursive, not a one-off checklist. Scenario findings inform trial structure and thresholds; trace ethnography captures interaction rhythm, scaffold revisions, and role handovers; longitudinal analysis tests whether κ and structural thresholds hold over time; comparative analysis prevents false generalisation. By triangulating across lenses—and explicitly incorporating the Bayesian synergy decomposition so that $\kappa > \theta$ serves as a quantitative trigger—researchers can determine with rigour whether an entangled ZPD has emerged and is maintained under varying conditions.

6.4.1. Brief note on mechanism. Riedl and Weidmann also show that Theory of Mind predicts collaborative ability (κ) and fluctuates within users, underscoring the need to model reciprocity dynamically rather than assume static profiles, further aligning with Entagogy's emphasis on bidirectional metacognition and within-session adaptivity.

6.5. Summary of Diagnostic Protocols

The Entagogy Diagnostic Protocol converts Entagogy's thresholds (adaptivity, guidance rhythm/latency, governance permeability, reciprocity, perturbation, and equity) into testable invariants, aligned with four research lenses (scenario, trace ethnography, longitudinal, comparative). Its purpose is to determine when genuine entanglement occurs, not when a system merely looks personalised. To operationalise this, we are indebted to and integrate Riedl and Weidmann [12]: a Bayesian IRT decomposition into individual ability (θ) and collaborative ability (κ). We treat $\kappa > \theta$ (beyond a pre-registered margin, with credible intervals) as a necessary statistical signal that must co-occur with structural indicators (within-session adaptivity and role-transfer reciprocity, sub-second rhythm, permeable governance, stability under perturbation).

We further advance study-level operationalisation though alternate solo and assisted trials on calibrated/near-isomorphic items (randomised, sparse) to estimate θ and κ; pre-register the entanglement rule (e.g., $\kappa - \theta > \delta$, 95% CrI + thresholds met). Validate via trace ethnography by time-locking reciprocity tags (two-way meta moves; micro handovers) to κ elevations. Test durability longitudinally (sustained/increasing κ with declining hint reliance) and under exogenous irritations (policy/content updates, teacher interventions, interface changes). Ensure equity by disaggregating κ by subgroup with pre-set margins and documenting corrective actions when gaps exceed thresholds.

With $\kappa > \theta$ as the quantitative trigger and Entagogy's thresholds as structural guards, the above protocol rigorously determines whether, and under what conditions, an e-ZPD has formed and is maintained.

7. Conclusion

By shifting attention from age-based pedagogical labels to the structural conditions under which a human cognitive system (HCS) and an AI semantic subsystem (AISS) genuinely couple, the framework of Entagogy resolves two chronic sources of noise in literature: the misclassification of responsiveness as adaptivity, and the false certainty that follows when pedagogy, andragogy, and heutagogy are mapped to demographics rather than autonomy and metacognitive readiness. In doing so, this paper offers researchers and builders a common language for when learning systems actually adapt, rather than merely appear to.

The contribution is both conceptual and operational. Conceptually, the entangled Zone of Proximal Development (e-ZPD) locates learning in the reciprocal perturbations between learner and system, where expertise is shared, roles transfer, and mediation is multimodal. Operationally, the Entagogy Diagnostic Protocol turns that concept into practice: adaptivity, guidance rhythm (latency), governance permeability, reciprocity, perturbation, and equity become measurable thresholds; $\kappa > \theta$, derived from a Bayesian synergy decomposition, becomes the necessary quantitative trigger that must co-occur with those structural signs to claim entanglement. This binds outcomes to mechanisms and protects the field from flattering false positives.

The implications are immediate. For research, pre-registered κ–θ decision rules, trace-ethnographic tagging of reciprocity, longitudinal durability checks, and perturbation tests make studies comparable and auditable across sites and models. For developers, the thresholds function as design requirements: engineer for within-session model updates, sub-second, semantically relevant feedback, and permeable, programmable governance, or accept plateauing at responsive branching.

Entagogy does not eliminate constraints. Its operation remains contingent on infrastructural capacity, regulatory environments, domain specificity, and cultural appropriateness. It also recognises the inevitability of autopoietic drift, embedding exogenous perturbations as a safeguard against closure and stagnation. This paper posits that these are not reasons for retreat, but conditions that demand careful instrumentation, iterative validation, and sustained monitoring.

Progress towards Bloom-level gains is unlikely to be achieved through sudden leaps in model performance. Rather, it will require the disciplined alignment of behavioural design, temporal rhythm, and governance architectures around demonstrable reciprocity; conditions that can be observed, measured, and reproduced across contexts.

With Entagogy, the central inquiry shifts from the reductive "Did AI increase learning?" to the more rigorous "At what points did entanglement manifest, by what indicators was it verified, and under which conditions did it endure?"

This reframing establishes a standard that is both replicable and auditable. Teachers speak in the language of pedagogy, and engineers in the language of algorithms. The bridge between them is absent. Entagogy provides that bridge and establishes a rigorous blueprint for crossing it with equity, transparency, and scale.

8. References

[1] Bloom, B. S. (1984). The 2 Sigma Problem: The Search for Methods of Group Instruction as Effective as One-to-One Tutoring. Educational Researcher, 13(6), 4–16. https://web.mit.edu/5.95/www/readings/bloom-two-sigma.pdf (Access Date: 7 April 2025).

[2] Létourneau, A., Deslandes Martineau, M., Charland, P., et al. (2025). A systematic review of AI-driven intelligent tutoring systems (ITS) in K-12 education. npj Science of Learning, 10, 29. DOI: 10.1038/s41539-025-00320-7.

[3] Latour, B. (2005). Reassembling the Social: An Introduction to Actor-Network Theory. Oxford: Oxford University Press.

[4] Bozkurt, A. (2024). Postdigital Educational Technology. In P. Jandrić (Ed.), Encyclopedia of Postdigital Science and Education. Cham: Springer. [Online]. Available at: DOI: 10.1007/978-3-031-35469-4_57-1 (Access Date: 24 May 2025).

[5] Barad, K. (2007). Meeting the Universe Halfway: Quantum Physics and the Entanglement of Matter and Meaning. Durham, NC: Duke University Press.

[6] Morales, L., and Zarabadi, S. (2024). Posthuman Educational Mappings: Agential Realism and Educational Practices. New York: Routledge.

[7] Luhmann, N. (1997). Die Gesellschaft der Gesellschaft. Frankfurt am Main: Suhrkamp.

[8] Burriss, S. K., and Leander, K. M. (2024). Critical posthumanist literacy: Building theory for reading, writing, and living ethically with everyday AI. Reading Research Quarterly, 59(1), 123–144.

[9] Pasquale, F. (2015). The Black Box Society: The Secret Algorithms That Control Money and Information. Cambridge, MA: Harvard University Press.

[10] Vygotsky, L. S. (1978). Mind in Society: The Development of Higher Psychological Processes. Cambridge, MA: Harvard University Press.

[11] Steiner-Khamsi, G. (2021). Externalisation and structural coupling: Applications in comparative policy studies in education. European Educational Research Journal, 20(6), 806–820.

[12] Riedl, C., and Weidmann, B. (2025, September 22). Quantifying Human-AI Synergy. PsyArXiv. DOI: 10.31234/osf.io/vbkmt_v1.

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