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Human–AI Symbiosis in Educational Communication: A Discursive Mapping of Cyborg Pedagogy and Human Cognition

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ABSTRACT

The integration of AI into education expands access to learning while intensifying cognitive dependence, trust miscalibration, and algorithmic control. This conceptual study employs critical interpretive synthesis and discursive mapping to examine the teacher–student–AI relationship. Findings show that human–AI symbiosis forms an asymmetrical communicative ecology with three possible outcomes: cognitive augmentation, cognitive substitution, or algorithmic domination. Educational value depends on AI literacy, verification, teacher guidance, transparency, and accountable governance.

ABSTRAK

Integrasi AI dalam pendidikan memperluas akses belajar sekaligus memunculkan risiko ketergantungan kognitif, penyalahgunaan kepercayaan, dan kontrol algoritmik. Studi konseptual ini menggunakan sintesis interpretif kritis dan pemetaan diskursif untuk menelaah relasi guru–mahasiswa–AI. Temuan menunjukkan bahwa simbiosis manusia–AI membentuk ekologi komunikasi yang asimetris dan menghasilkan tiga kemungkinan: augmentasi kognitif, substitusi kognitif, atau dominasi algoritmik.

INTRODUCTION

A university student who consults a generative artificial intelligence system no longer encounters technology merely as a storage device, search engine, or channel for retrieving information. Through prompting, follow-up questioning, interpretation, and revision, the learner enters a communicative exchange in which AI may provide explanations, recommendations, evaluations, and apparently personalised feedback (Wang et al., 2025). Unlike earlier educational technologies that primarily stored or transmitted content, conversational AI directly participates in the linguistic production of academic knowledge. Communication, cognition, and pedagogical action are therefore increasingly distributed across teachers, learners, and computational systems (Herari et al., 2026; Nuryadin, 2023).

This transformation is already visible in Bangladesh. In a qualitative study of 20 Khulna University students, Hasib & Islam (2025) found that ChatGPT was used for assignments, research, presentations, information seeking, and non-academic purposes because students considered it efficient and accessible. Participants nevertheless encountered false references, standardized feedback, and uncertainties surrounding responsible attribution, while some reported strategies for bypassing plagiarism-detection mechanisms. AI may therefore operate simultaneously as an academic assistant, conversational partner, persuasive knowledge source, and mechanism through which academic integrity is renegotiated.

The Bangladesh case reveals a central contradiction in AI-supported education. The speed, fluency, responsiveness, and apparent personalization that make conversational AI attractive may also make its limitations less visible to learners. Students can receive answers that appear coherent and authoritative without being able to determine whether they are accurate, contextually appropriate, or intellectually sufficient. Human–AI interaction consequently broadens access to educational support while creating uncertainty concerning knowledge, responsibility, and the depth of learning.

Although generative AI introduces novel technological capabilities, the reorganization of pedagogical authority is not historically unprecedented in South Asia. Brahmanical and later Hindu learning traditions developed through relationships among teachers, disciples, texts, oral practices, ethical formation, and everyday experience. The guru–shishya tradition emphasised sustained proximity, recitation, observation, practice, discipline, and the cultivation of intellectual and moral character (Mookerji, 1998). Learning was therefore understood not merely as information transfer but as relational formation shaped by presence, communication, and trust.

Classical South Asian traditions also contained dialogic practices in which questioning, response, argument, and reflection contributed to knowledge formation. The conversation between Krishna and Arjuna in the Bhagavad Gita, for example, symbolically represents learning as the articulation of uncertainty and the development of ethical judgment through dialogue. Nevertheless, the guru–shishya relationship should not be romanticized as egalitarian, because teachers retained substantial authority and access to education was influenced by social position, gender, institutional location, and lineage (Mookerji, 1998; Prickett, 2007). Its relevance lies in demonstrating that educational communication has always been structured by culturally specific distributions of authority.

Islamic educational traditions subsequently diversified the pedagogical landscape through maktab, madrasa, Sufi, scholarly, and master–disciple networks. The transmission of ʿilm involved oral instruction, recitation, memorization, textual commentary, interpretation, disputation, and ethical cultivation, while teacher–student relations contributed to scholarly authority and community formation (Hefner, 2000). In South Asia, Sufi networks and communities of ʿulama supported written and oral learning, while madrasas developed specialised curricula and forms of scholarly certification (Sanyal, 2021). Hindu and Islamic pedagogies were neither internally uniform nor entirely separate, but both demonstrate that education has long been inseparable from cultural legitimacy, hierarchy, and institutional power.

British colonial rule produced another reconfiguration by reorganising educational language, curriculum, institutions, and political purpose. Macaulay's 1835 Minute on Indian Education supported English-language instruction and Western knowledge while envisioning an intermediary class serving colonial administration (Macaulay, 1835). Colonial education did not immediately eliminate indigenous practices, but it established new hierarchies among languages, disciplines, texts, and authorised forms of knowledge. Curriculum and literary instruction consequently functioned as both pedagogical resources and instruments for producing particular identities and political relationships (Kumar, 2005; Viswanathan, 2015).

This historical trajectory shows that pedagogical authority in the Indian subcontinent has repeatedly changed alongside political, institutional, media, and economic transformations. Residential mentorship, oral and textual scholarship, religious institutions, colonial classrooms,

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mass education, digital platforms, and generative AI represent different configurations through which knowledge is defined, communicated, evaluated, and governed. Generative AI is distinctive in that it not only conveys educational messages but also generates responses and participates directly in communicative exchanges. The teacher–student relationship is consequently developing into a teacher–student–AI configuration in which communicative participation expands while accountability remains asymmetrically human.

Evidence beyond Bangladesh reinforces this concern. Stojanov (2023) experienced ChatGPT as a responsive and motivating learning scaffold, but also found its explanations superficial, inconsistent, and occasionally contradictory, producing cognitive flow alongside an overestimation of understanding. Similarly, Sun et al., (2024) found that students using ChatGPT in programming interacted more frequently with automated feedback and debugging processes, yet their performance did not differ significantly from that of students engaged in self-directed learning. Increased human–AI interaction should therefore not automatically be equated with deeper cognition, improved performance, or greater autonomy.

The institutional urgency of this transformation is reflected in UNESCO's concern that generative AI has developed more rapidly than many educational regulations and institutional capacities, particularly regarding privacy, validation, inclusion, agency, and responsible use (UNESCO, 2023). Yet current debate remains divided between technological optimism and technological alarmism, overlooking how educational consequences emerge through prompting, interpretation, credibility, feedback, and the allocation of responsibility. The novelty of this paper lies in approaching human–AI symbiosis as a problem of educational communication and examining the teacher–student–AI relationship as an asymmetrical ecology of cognition, meaning-making, and authority. Accordingly, this research emphatically puts emphasis on the technical accuracy and learning outcomes in association with under-theorizing educational communication, specifically, how Large Language Models (LLMs) impact the triadic negotiation among teachers, students, and computational agents or AI. To connect this conceptual gap, this paper addresses the following research questions:

1. How is educational communication conceptualized and reconfigured within the emerging triadic teacher–student–AI relationship?
2. What dominant discursive categories shape scholarly and institutional representations of human–AI symbiosis in learning contexts?

3. In what ways do cyborg pedagogy, distributed cognition, critical pedagogy, and human–machine communication integrate to explain the cognitive and political outcomes of this symbiosis?

METHODOLOGY

This study employed a critical conceptual research design combining theory synthesis with model development. Conceptual research generates new explanations by clarifying, connecting, and critically reorganizing existing theoretical relationships rather than collecting primary empirical data or testing measurable effects (Jaakkola, 2020). The study integrated cyborg and posthuman pedagogy, distributed cognition, critical pedagogy, and human–machine communication to examine human–AI symbiosis as a cognitive, communicative, political, and institutional relationship. Its analytical corpus comprised peer-reviewed conceptual and empirical publications, foundational scholarly works, historical sources on South Asian pedagogy, and relevant international policy documents selected purposively for their relevance to educational interaction, cognitive distribution, communicative agency, epistemic authority, datafication, and institutional control.

Drawing on critical interpretive synthesis, discursive mapping was conducted iteratively to examine how the selected sources represented AI as a tool, a cognitive extension, a communicative participant, a knowledge authority, or a mechanism of institutional governance. This approach is appropriate for heterogeneous evidence because it moves beyond descriptive summary to identify assumptions, contradictions, and relationships across theoretical and empirical accounts (Dixon-Woods et al., 2006). The analysis proceeded by identifying central claims and observations, interpreting them through the four theoretical perspectives, comparing convergent and contradictory positions, and synthesizing the resulting patterns into the teacher–student–AI ecology, three systemic vulnerabilities, and three possible outcomes: cognitive augmentation, cognitive substitution, and algorithmic domination. Because the objective was interpretive theory-building rather than exhaustive evidence aggregation, the study does not claim to constitute a systematic review (Snyder, 2019).

Published cases from Bangladesh, Pakistan, programming education, and autoethnographic learning were used as secondary empirical anchors rather than as a representative cross-national sample. They were selected because they provided contrasting evidence concerning academic assistance, cognitive offloading, trust, feedback, performance, and dependency, thereby illustrating how conceptual relationships may operate under different conditions without supporting statistical generalization (Siggelkow, 2007). Analytical credibility was strengthened through comparison among theoretical, empirical, historical, and policy sources, attention to evidence challenging celebratory accounts of symbiosis, and repeated examination of emerging interpretations against the original publications.

LITERATURE REVIEW

Research on artificial intelligence in education has historically been dominated by questions of technological functionality, instructional efficiency, and measurable learning outcomes. Zawacki-Richter et al. (2019) found that higher education research primarily concentrated on profiling and prediction, assessment and evaluation, adaptive systems, and intelligent tutoring, while educators and pedagogical relationships received comparatively limited attention. A subsequent meta-systematic review indicates that the field continues to privilege personalization, prediction, and technological performance despite growing concerns regarding ethics, contextual sensitivity, methodological rigor, and interdisciplinary participation (Bond et al., 2024). Existing scholarship has therefore become increasingly sophisticated in identifying what educational AI can perform, but remains less developed in explaining how it reorganises cognition, authority, communication, and institutional power.

The movement from AI-directed to AI-supported and AI-empowered education represents an important attempt to reposition learners as active participants rather than recipients of automated instruction (Ouyang & Jiao, 2021). Nevertheless, the designation of learners as “collaborators” or “leaders” does not necessarily demonstrate that they possess meaningful authority over how AI is designed, implemented, or interpreted. Interactive features may increase participation while still directing learners toward predefined categories, automated recommendations, and platform-specific forms of knowledge. Human–AI collaboration should therefore be evaluated not only through the presence of interaction but through the distribution of cognitive labor, epistemic authority, and decision-making capacity (Boyd & Markowitz, 2025).

Generative AI intensifies these concerns by moving artificial intelligence from relatively invisible functions such as prediction and analytics into direct linguistic interaction with learners (Tao, et al., 2026). Large language models can assist with explanations, feedback,

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brainstorming, translation, content generation, and personalized support, while simultaneously producing misinformation, bias, opacity, and academically inappropriate forms of dependency (Farrokhnia et al., 2024; Kasneci et al., 2023). These benefits and risks are not separate consequences because the speed, fluency, and responsiveness that make generative AI attractive can also make its limitations more difficult to recognise. Across the literature, this tension produces three interconnected systemic vulnerabilities.

Attentional Capture and Cognitive Offloading

The first vulnerability concerns the possibility that AI-supported learning may move from cognitive assistance toward cognitive substitution. Cognitive offloading refers to the use of external resources or actions to reduce the internal demands of remembering, processing, or problem-solving (Risko & Gilbert, 2016). Offloading is not inherently detrimental because educational tools have always extended human cognitive capacity; however, it becomes problematic when learners routinely delegate interpretation, argument construction, verification, and decision-making without retaining reflective oversight. The immediate availability of fluent AI responses can therefore create conditions in which convenience becomes more influential than sustained cognitive engagement.

This risk is reinforced by automation bias, through which users may privilege algorithmic suggestions even when contradictory information or alternative reasoning is available (Parasuraman & Manzey, 2010). Within educational environments, automation bias may appear when students accept AI-generated answers because they are coherently phrased, rapidly produced, or presented with apparent confidence. Repeated reliance may gradually reposition AI from a resource for inquiry into the default point of departure and conclusion of intellectual activity. The central concern is consequently not whether learners use AI, but whether such use preserves the capacity to formulate questions, tolerate uncertainty, evaluate evidence, and construct independent judgments.

Attentional capture and cognitive offloading should therefore be treated as related but distinct processes. Attentional capture describes how an always-available and highly responsive system may become the preferred focus of learning activity, whereas cognitive offloading describes the transfer of mental work to that system. When combined, they risk narrowing learning into prompt production and output consumption rather than sustained interpretation

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and dialogic reflection. Human–AI symbiosis cannot consequently be inferred from frequent interaction because intensive use may indicate productive cognitive extension, avoidant delegation, or a combination of both.

Trust Calibration and Epistemic Authority

The second vulnerability concerns how learners determine when an AI system should be trusted. Research on human trust in AI demonstrates that reliance is influenced not only by technical performance but also by perceived competence, transparency, embodiment, interaction quality, and the expectations users bring to automated systems (Glikson & Woolley, 2020). Trust calibration therefore requires neither unconditional confidence nor categorical rejection, but alignment between the system’s actual reliability and the degree of reliance placed upon it. In educational communication, this alignment is difficult because learners may lack sufficient disciplinary knowledge to identify subtle inaccuracies in an apparently convincing response (Sohail & Lin, 2025).

Large language models make this problem particularly significant because linguistic fluency can be mistaken for understanding or epistemic reliability. (Bender et al., 2021) caution that language models generate textual patterns without grounding them in communicative intention or human forms of meaning, while (Kasneci et al., 2023) identify hallucination, bias, and opacity as substantial challenges for educational use. A response may therefore be grammatically polished and contextually plausible while remaining factually incorrect, conceptually superficial, or normatively problematic. The system’s communicative persuasiveness may exceed its epistemic dependability.

This tension reconfigures epistemic authority within education. Teachers are no longer the only visible source of explanation, yet AI does not become an accountable knowledge authority merely because learners perceive it as one. Learners must instead undertake continuous verification, comparison, and contextual evaluation, potentially reducing the cognitive relief that automation promises to provide. Trust calibration should therefore be understood as an educational competency requiring AI literacy, disciplinary judgment, source evaluation, and awareness of how linguistic confidence can conceal uncertainty.

Surveillance, Control, and Power Dynamics

The third vulnerability emerges from the data infrastructures required to make educational AI adaptive and personalised. AI-supported systems frequently depend upon the collection, classification, and analysis of learner behaviour, performance, interaction histories, and predictive profiles. Akgun & Greenhow (2022) identify privacy, transparency, bias, autonomy, and accountability as central ethical concerns in educational AI. Personalisation must therefore be examined not only as pedagogical assistance but also as a process through which students become increasingly measurable, predictable, and institutionally visible.

Learning analytics research has long demonstrated that educational data practices are inseparable from ethical questions concerning consent, institutional responsibility, vulnerability, and the unequal distribution of benefits and risks (Slade & Prinsloo, 2013). Students may value data-informed educational support while simultaneously demanding greater knowledge of what is collected, who may access it, and how it influences institutional decisions (Ifenthaler & Schumacher, 2016). The central issue is not simply whether monitoring improves learning outcomes, but whether learners can meaningfully understand, challenge, or refuse the conditions under which their activities are converted into data. Personalised support can otherwise become the legitimising language through which surveillance is normalised.

These dynamics also complicate claims that teachers, students, and AI constitute equal partners. AI systems remain embedded within commercial platforms, institutional procurement decisions, proprietary models, and governance structures that individual users rarely control. Teachers and learners may appear to retain agency while operating within interfaces that delimit available choices, rank information, and record behaviour. Human–AI symbiosis is therefore not merely an interaction between two agents but an institutional arrangement shaped by asymmetrical capacities to design, monitor, classify, and contest technological systems.

THEORETICAL FRAMEWORK

Human–AI symbiosis cannot be adequately explained through a single theoretical tradition because it simultaneously concerns ontological boundaries, cognitive processes, institutional power, and communicative relations. This study therefore develops an integrative analytical framework from four established bodies of scholarship: cyborg and posthuman pedagogy, distributed cognition, critical pedagogy, and human–machine communication. These perspectives are not treated as interchangeable, nor are they assembled merely to provide a broad literature summary. Instead, each addresses a distinct analytical problem and corrects the limitations of the others: posthumanism explains entanglement, distributed cognition specifies cognitive distribution, critical pedagogy interrogates power, and human–machine communication clarifies interaction and meaning-making.

Cyborg and Posthuman Pedagogy: Human–Technology Entanglement

Cyborg and posthuman scholarship challenges the assumption that the human learner is an autonomous and self-contained subject who merely uses technology from the outside. Haraway's cyborg destabilizes categorical separations between organism and machine, while Hayles demonstrates that posthumanism should not be reduced to the disappearance of the body or the replacement of humans by information systems (Haraway, 1995; Hayles, 1999). The relevant theoretical point is therefore not that learners literally become machines, but that their actions, identities, and capacities are increasingly constituted through material and informational relations with technological systems. In educational contexts, this lens redirects attention from AI as an external instructional aid toward the sociotechnical conditions through which learning is produced.

Cyborg pedagogy further extends this critique by treating technological hybridity as a site of both possibility and resistance rather than as evidence of inevitable progress. Garoian & Gaudelius (2001) position the cyborg as a critical pedagogical metaphor through which the social, political, and cultural assumptions embedded in information technologies can be exposed and questioned. This position is important because a celebratory language of "symbiosis" may otherwise naturalize AI adoption and obscure the corporate infrastructures, training data, interface designs, and institutional decisions that condition the relationship. Accordingly, this study uses cyborg pedagogy to conceptualize the learner–AI relation as an entanglement but rejects the deterministic conclusion that technological integration is automatically reciprocal, emancipatory, or equal.

The posthuman perspective also prevents the analysis from restoring human exceptionalism under the language of human-centred AI. However, decentring the human does not require abandoning questions of embodiment, responsibility, or vulnerability. Hayles's critique of disembodied information is especially relevant because generative AI can create the impression that knowledge exists independently of the bodies, histories, labour, and cultural contexts through which it is produced. Thus, the posthuman lens establishes the ontological condition of human–AI interdependence while leaving open the political question of who designs, owns, and governs that interdependence.

Distributed Cognition: Cognitive Processes Across Human–AI Assemblages

Distributed cognition provides a more precise account of how cognitive work may extend beyond the individual learner. Hutchins (1995) argues that cognition can be located within coordinated activity systems involving people, representational artefacts, and material environments rather than exclusively inside an individual mind. Clark & Chalmers (1998) similarly propose that external resources may become components of cognitive processes when they are reliably integrated into thinking and action. Applied to AI-mediated education, these arguments make it possible to analyse prompts, generated responses, stored information, feedback, revision, and verification as parts of a wider cognitive system.

This framework nevertheless requires stricter conditions than the simple claim that any use of AI constitutes cognitive extension. A generative system may support memory, comparison, explanation, or idea generation, yet it may also produce inaccurate outputs, conceal the basis of its responses, or encourage users to delegate judgments that they remain responsible for making. The central distinction is therefore between cognitive extension, in which an external resource supports and remains integrated with reflective reasoning, and cognitive substitution, in which the learner relinquishes epistemic monitoring to an opaque system. Human–AI symbiosis should not be inferred from frequency of use alone; it must be examined through the quality of coordination, verification, and metacognitive control.

Critical Pedagogy: Autonomy, Power, Surveillance, and Domination

Critical pedagogy addresses the normative and political questions that posthuman and cognitive accounts may leave underdeveloped. Freire's critique of banking education rejects pedagogical relations in which knowledge is deposited by an authoritative teacher into passive learners and instead advances dialogue, problem-posing, and critical consciousness (Freire et al., 2018). AI may appear to disrupt the teacher's monopoly over knowledge by providing learners with alternative explanations, immediate feedback, and opportunities for self-directed inquiry. Yet the weakening of visible teacher authority does not necessarily eliminate domination; it may transfer authority to less visible algorithmic, institutional, and commercial systems.

A critical analysis must therefore ask who defines the objectives, classifications, and acceptable forms of knowledge embedded in AI-supported education. Williamson & Eynon, (2020) demonstrate that AI in education has developed through intersecting traditions of cognitive science, computational modelling, educational technology, and policy rather than through a politically neutral sequence of technical improvements. Selwyn (2019) similarly cautions against evaluating educational AI only through efficiency or performance by emphasizing the social, emotional, professional, and political dimensions of teaching. These critiques challenge accounts of symbiosis that treat the human and AI as two isolated partners while ignoring platform ownership, institutional procurement, data extraction, and asymmetries in the ability to contest automated decisions.

Critical pedagogy also provides the basis for examining surveillance and datafication. Learning analytics, adaptive systems, and AI-mediated assessments may transform learner activity into continuously monitored data, thereby making pedagogical support inseparable from classification and institutional visibility. The critical issue is not simply whether data collection improves learning, but whether learners understand the process, can refuse or challenge it, and retain meaningful control over how their data and performances are interpreted. In this framework, autonomy is not defined as freedom from technology but as the capacity to participate knowingly and contestably in the conditions under which technology mediates learning.

Human–Machine Communication: Interaction, Meaning-Making, and Communicative Agency

Human–machine communication supplies the communication-theoretical component required by the manuscript's revised title. Guzman & Lewis (2020) argue that communicative AI cannot be adequately understood through models that treat technology only as a channel for human messages because users increasingly encounter AI systems as sources of responses, recommendations, voices, and social cues. Their framework directs attention to the functional

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ways people interpret machines as communicators, the relational dynamics formed through repeated interaction, and the ontological questions produced when boundaries between human and machine communicators become unstable. This perspective allows the educational encounter to be analyzed not merely as technology-assisted instruction but as a communicative process.

In the teacher–student–AI configuration, AI participates in communication by generating explanations, reframing questions, evaluating text, simulating dialogue, and providing personalized feedback. Research on robots in classrooms has demonstrated that the perceived identity and role of a technological agent can influence judgments of credibility and learning, indicating that the source of a message matters alongside its informational content (Edwards et al., 2016). However, describing AI as a communicative participant should not be confused with granting it human intentionality, consciousness, or moral accountability. Its communicative agency is operational and attributed: the system produces consequential messages, while its capacities remain structured by models, data, designers, institutions, and user prompts.

This distinction is essential for analysing trust calibration and epistemic authority. Learners may respond socially to fluent language, interpret confident outputs as expertise, or treat personalized feedback as evidence of understanding, even when the system cannot assume responsibility for the consequences of its advice. Human–machine communication therefore asks how credibility is constructed, how users negotiate meaning with nonhuman interlocutors, and how responsibility is distributed when machine-generated messages shape educational decisions. It also clarifies that dialogue with AI is asymmetrical: the learner is embodied, socially accountable, and educationally vulnerable, whereas the system's apparent conversational presence is produced through computational and institutional arrangements.

Integrating the Four Perspectives

Taken together, the four perspectives conceptualize human–AI symbiosis as a negotiated sociotechnical relation rather than a naturally harmonious partnership. Cyborg and posthuman pedagogy identifies the entanglement of humans and technologies; distributed cognition examines the allocation of cognitive labour; critical pedagogy exposes the power relations that organize such allocation; and human–machine communication explains how the relation is

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enacted through messages, feedback, source perception, and meaning-making. The framework therefore analyses the teacher–student–AI triad through four questions: how actors become entangled, how cognition is distributed, how power is exercised, and how communicative agency is attributed.

Table 1.Integrative Theoretical Framework for Analysing Human–AI Symbiosis in Educational Communication

Theoretical Perspective	Main Analytical Function	Critical Question
Cyborg/posthuman pedagogy	Explains human–technology entanglement	How does AI become constitutive of pedagogical practice and learner identity?
Distributed cognition	Explains the distribution of cognitive labour	Which cognitive processes are extended, shared, or surrendered to AI?
Critical pedagogy	Examines autonomy, power, surveillance, and domination	Who controls the system, data, knowledge categories, and educational decisions?
Human-machine communication	Explains interaction, feedback, meaning-making, and communicative agency	How is AI perceived and negotiated as a source or participant in communication?

Source: Researcher, 2026

The original contribution of this study lies not in claiming to invent these four theoretical traditions, but in synthesizing them into an analytical architecture appropriate for educational communication. This synthesis produces a critical definition of human–AI symbiosis as a condition in which human and computational capacities become interdependent through recurring cognitive and communicative exchanges while remaining unequal in embodiment, accountability, institutional power, and control. Such a definition avoids both technological romanticism and categorical rejection by requiring analysis of when AI augments learning, when it displaces judgment, when it broadens dialogue, and when it intensifies surveillance or dependency. Human–AI symbiosis is therefore treated as an unresolved field of negotiation whose educational value depends on reflective judgment, contestable authority, and meaningful human agency.

FINDINGS AND DISCUSSION

The discursive mapping indicates that human–AI symbiosis does not represent a single or universally beneficial model of educational transformation. Instead, it describes a contested relationship in which technological assistance, cognitive delegation, communicative authority, and institutional control are combined in different proportions. The educational significance of

AI therefore cannot be determined merely by whether students and teachers use it, but by how cognition, meaning-making, responsibility, and decision-making are reorganised through that use. The findings reveal three interconnected movements: the formation of a teacher–student–AI ecology, the emergence of systemic vulnerabilities, and the redistribution of communicative and pedagogical authority.

The Hybrid Educational Ecology: Entanglement, Asymmetry, and the Augmentation–Substitution Continuum

The first analytical finding is that contemporary educational communication is gradually moving beyond the conventional teacher–student dyad. Generative AI can now answer questions, produce explanations, reformulate arguments, evaluate text, recommend revisions, and simulate personalised feedback. Through these functions, the system enters processes that were previously mediated primarily by teachers, peers, textbooks, and other human-authored academic sources. Education is consequently developing into a teacher–student–AI ecology in which communicative exchanges and cognitive activities circulate among human and computational participants.

The Bangladesh case illustrates that this ecology is already embedded in students' everyday academic practices. Students at Khulna University reported using ChatGPT for assignments, research, presentations, and information seeking, demonstrating that AI was involved not only in accessing information but also in shaping how academic material was organised and communicated (Hasib & Islam, 2025). The system consequently occupied several roles at once: search assistant, writing partner, feedback source, and apparent knowledge authority. However, the occurrence of fabricated references and standardised responses showed that communicative participation did not guarantee epistemic reliability.

This finding supports the view that AI should no longer be examined solely as a neutral educational tool. A tool is conventionally understood as remaining under the visible direction of its user, whereas generative AI produces responses that can redirect questions, introduce categories, frame problems, and influence subsequent decisions. Its outputs are therefore communicatively consequential even though the system does not possess human consciousness, embodiment, or moral responsibility. AI participates operationally in communication, while accountability for accepting, verifying, and applying its messages continues to fall upon human actors.

The emergence of this hybrid ecology confirms human–technology entanglement, but it does not establish equality between humans and AI. Learners may depend on AI-generated explanations, yet they remain responsible for academic accuracy and ethical conduct. Teachers may be expected to supervise AI-supported learning, although they have limited access to students' private interactions with generative systems. Meanwhile, AI models remain shaped by developers, training data, commercial infrastructures, and institutional policies that users rarely control.

Human–AI symbiosis is therefore structurally asymmetrical. Humans bear the educational, ethical, and social consequences of error, while the system generates outputs without assuming responsibility for them. Students and teachers may interact directly with AI, but platform providers and institutional actors govern many of the conditions through which that interaction occurs. The relationship is interdependent at the level of practice but unequal at the levels of embodiment, accountability, transparency, and control.

This asymmetry is particularly visible when cognitive activity is distributed between learners and AI. Generative systems can extend human capacity by supporting brainstorming, linguistic reformulation, comparison, retrieval, feedback, and the exploration of alternative interpretations. Such assistance may reduce unnecessary cognitive load and enable learners to focus on disciplinary judgment or higher-level conceptual work. In this condition, AI functions as cognitive augmentation because external support remains connected to reflective human oversight.

Distributed cognition becomes pedagogically problematic, however, when assistance develops into substitution. Cognitive substitution occurs when learners delegate not only information retrieval but also problem formulation, argument construction, evaluation, and final judgment. The learner may remain technically involved by writing prompts and selecting outputs, but this limited participation does not necessarily demonstrate intellectual ownership. Prompting can become a procedural activity that conceals the transfer of substantive reasoning to the system.

The distinction between augmentation and substitution is supported by evidence from programming education. Sun et al. (2024) found that students using ChatGPT interacted more frequently with automated feedback and debugging processes, yet their programming performance did not differ significantly from that of students engaged in self-directed learning. Increased interaction therefore reflected a more intensive human–AI feedback loop but did not automatically demonstrate deeper learning. Communicative frequency and cognitive quality should consequently be treated as analytically distinct.

The educational value of distributed cognition depends less on how much work is transferred to AI than on which forms of judgment remain under human control. AI use is augmentative when learners formulate the problem, interrogate the response, compare alternative evidence, and remain capable of explaining the resulting conclusion. It becomes substitutive when the system defines both the question and the answer while the learner primarily performs selection, editing, or submission. Human–AI symbiosis should therefore be understood as a continuum ranging from reflective augmentation to procedural dependency rather than as a stable state of collaboration.

Three Systemic Vulnerabilities of Human–AI Educational Communication

The second finding is that the teacher–student–AI ecology generates three interconnected vulnerabilities. These vulnerabilities concern the learner's capacity to sustain attention and reasoning, the credibility attributed to machine-generated knowledge, and the institutional infrastructures through which AI-supported education is governed. They should not be interpreted as external side effects that appear only when technology is misused. Rather, they emerge from the same speed, personalisation, responsiveness, and data processing that make AI educationally attractive.

1. **Attentional Capture and Cognitive Offloading**

The first vulnerability occurs when AI becomes the default gateway through which learners approach academic problems. The system's constant availability and immediate responsiveness may gradually reduce students' willingness to remain with uncertainty, struggle with difficult texts, or construct an answer before seeking assistance. Attentional capture does not necessarily mean that AI distracts students from learning; it may instead reorganise learning around the expectation of rapid machine response. The learner's attention becomes oriented toward generating effective prompts and processing outputs rather than sustaining independent inquiry.

Cognitive offloading becomes problematic when the externalisation of mental work removes the intellectual difficulty through which understanding is developed. Reading, comparing evidence, revising an argument, and confronting contradiction are not merely inefficient stages preceding an answer; they are constitutive parts of learning. When AI produces a polished response before the learner has developed a conceptual position, the system may replace rather than support this formative struggle. Efficiency can therefore conceal a decline in the learner's opportunity to practise reasoning.

The study of university students by Abbas et al. (2024) helps illustrate this vulnerability. Academic workload and time pressure were associated with greater ChatGPT use, which was in turn related to procrastination, reported memory difficulties, and lower academic performance. These relationships do not establish that every use of AI causes cognitive decline, but they show that AI adoption often occurs under conditions that reward task completion over reflective engagement. The same technology may consequently operate as a scaffold under one pedagogical design and as an avoidance mechanism under another.

2. Trust Calibration and Epistemic Authority

The second vulnerability concerns the gap between communicative fluency and epistemic reliability. Generative AI can produce coherent, personalised, and confident responses even when its information is inaccurate or insufficiently grounded. Learners may therefore attribute credibility to the system because of how the answer is communicated rather than because of the quality of the underlying evidence. The persuasive characteristics of the message can exceed the reliability of the knowledge it contains.

This problem was visible in the Bangladesh case, where students encountered false references while continuing to value ChatGPT's accessibility and usefulness (Hasib & Islam, 2025). It also appeared in Stojanov's (2023) autoethnographic study, in which responsive dialogue supported engagement but encouraged an overestimation of understanding and made contradictions difficult to recognise during the interaction. These cases show that AI may acquire educational authority before it has demonstrated consistent accuracy. The critical tension is therefore not simply trust versus mistrust, but whether the degree of reliance corresponds to the system's actual reliability.

Trust calibration requires learners to move between two potentially harmful extremes. Blind reliance may lead them to accept fabricated evidence, biased framing, or superficial explanations, while categorical distrust may prevent them from using AI for legitimate forms of assistance. The appropriate position is conditional trust, in which outputs are treated as provisional contributions requiring comparison, contextualisation, and verification. Such calibration depends on disciplinary knowledge, source literacy, and the capacity to recognise that linguistic confidence is not equivalent to truth.

This vulnerability also redistributes epistemic labour. AI promises cognitive relief by producing immediate answers, yet unreliable output requires learners to undertake continuous verification. The system may therefore reduce the effort required to generate information while increasing the effort required to determine whether that information deserves acceptance. Human–AI symbiosis becomes educationally productive only when verification remains an integral part of communication rather than an optional correction after the output has been used.

3. Surveillance, Control, and Power Dynamics

The third vulnerability concerns the institutional conditions that support AI personalization and automated educational decision-making. Systems that provide adaptive feedback or learning analytics frequently depend on the collection of interaction histories, performance data, behavioral patterns, and predictive profiles. Personalization and surveillance are therefore not necessarily opposing functions; they may be produced by the same infrastructure. The more precisely a system responds to the learner, the more extensively the learner may need to become visible as data.

This visibility creates questions that cannot be resolved through individual AI literacy alone. Students may know how to verify an answer while remaining unable to determine what data a platform collects, how long the information is stored, or whether it contributes to profiling and institutional evaluation. Teachers may also use dashboards or automated recommendations without fully understanding how classifications were produced. Human oversight becomes symbolic when human actors are expected to approve decisions generated through processes they cannot meaningfully inspect.

The power of educational AI is therefore located not only in the content of its outputs but also in the infrastructure that organises access, visibility, and classification. Platform developers determine model architecture, institutions determine adoption and policy, teachers shape classroom implementation, and students operate within conditions largely established by

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others. The teacher–student–AI ecology consequently contains actors with highly unequal capacities to design, monitor, and contest the system. Symbiosis may become a legitimising term that obscures these asymmetries when institutional power is not made analytically visible.

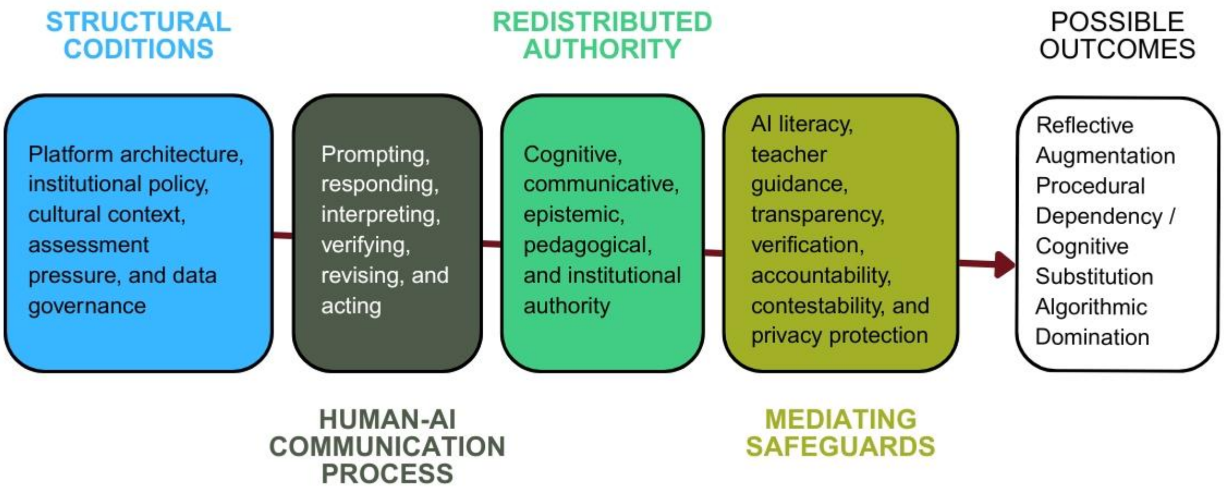

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Figure 1. Redistributed Authority in Human–AI Educational Communication: A Proposed Framework (Author, 2026)

Figure 1 presents the proposed framework derived from the discursive mapping and critical synthesis undertaken in this study. The framework conceptualizes human–AI symbiosis in educational communication not as a fixed or inherently beneficial condition but as a structured, mediated relationship shaped by institutional, technological, and pedagogical factors. It explains how the emerging teacher–student–AI ecology is produced, how authority is redistributed within it, and under what conditions the relationship becomes educationally productive or problematic.

The first component, structural conditions, refers to the broader context in which human–AI interaction occurs. These conditions include platform architecture, institutional policy, cultural context, assessment pressure, and data governance. Human–AI educational communication does not occur in a neutral environment, because the terms of interaction are already shaped by system design, institutional expectations, and unequal access to technological resources. Before any prompt is entered, these conditions influence what kinds of communication are possible, encouraged, or constrained.

The second component, the human–AI communication process, captures the recurring sequence through which educational interaction unfolds: prompting, responding, interpreting,

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verifying, revising, and acting. This sequence highlights that AI-supported learning is not reducible to information retrieval. Rather, it is a communicative process in which meaning is continuously negotiated through interaction. The educational value of this process depends not on the mere presence of AI, but on whether interpretation and verification remain active human responsibilities.

The third component, redistributed authority, represents the central analytical contribution of the framework. In AI-mediated education, authority is no longer concentrated solely in teachers or formal academic texts. Instead, it becomes distributed across cognitive, communicative, epistemic, pedagogical, and institutional dimensions. Learners retain agency in formulating prompts and selecting responses, teachers remain responsible for educational design and guidance, and AI systems exercise operational communicative influence through the generation of explanations, feedback, and recommendations. However, this redistribution is asymmetrical, since AI participates in communication without assuming moral or pedagogical accountability.

The fourth component, mediating safeguards, identifies the conditions necessary to preserve meaningful human agency. These include AI literacy, teacher guidance, transparency, verification, accountability, contestability, and privacy protection. The framework argues that productive symbiosis does not emerge automatically from technological integration. It depends on whether these safeguards enable learners and teachers to interpret, question, and govern AI-supported communication critically.

Finally, the framework leads to possible outcomes. These outcomes range from cognitive augmentation, in which AI extends reflective learning, to cognitive substitution, in which learners delegate substantial reasoning to the system, and algorithmic domination, in which technological and institutional systems shape learning without sufficient transparency or contestability. Figure 1 therefore illustrates that human–AI symbiosis is not a singular outcome, but a contingent process whose educational value depends on how communication, authority, and governance are organised.

CONCLUSION

This study demonstrates that human–AI symbiosis is reconfiguring educational communication from a predominantly teacher–student relationship into a teacher–student–AI ecology in which cognition, meaning-making, feedback, and authority circulate across human and computational actors. This redistribution does not establish symmetry, because AI may exercise operational communicative influence while teachers and learners continue to bear epistemic, ethical, and pedagogical responsibility. The analysis identifies three interrelated vulnerabilities (attentional capture and cognitive offloading, trust miscalibration, and surveillance-based institutional control) which show that the same responsiveness and personalisation that make AI educationally attractive may also produce dependency and less visible forms of authority. The proposed framework therefore positions cognitive augmentation, cognitive substitution, and algorithmic domination as contingent outcomes shaped by structural conditions, communicative practices, redistributed authority, and safeguards such as teacher guidance, verification, transparency, accountability, contestability, and privacy protection.

The study is limited by its critical conceptual design, purposively selected corpus, and reliance on published secondary cases rather than primary classroom data or a representative cross-national sample. Its framework consequently offers an interpretive explanation rather than a validated causal model, and the selected cases cannot capture the full diversity of institutional, disciplinary, cultural, and technological conditions surrounding educational AI. Future research should empirically examine the proposed relationships through classroom observation, interviews, experiments, longitudinal studies, and cross-cultural comparison, particularly by investigating how learners move between augmentation and substitution and how institutional data practices may intensify algorithmic domination. Such research should also test whether reflective participation, calibrated trust, and accountable governance can preserve human judgment while allowing AI to extend rather than displace the communicative and cognitive purposes of education.

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