

Large language models as collaborative learning partners in higher education: a theoretical framework

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ABSTRACT: The integration of Large Language Models (LLMs) into higher education environments reveals notable challenges within existing educational technology frameworks. Current theoretical models conceptualize artificial intelligence as an instrumental tool that supports human learning processes, yet numerous empirical studies demonstrate that LLMs function as collaborative learning partners with reciprocal agency, dynamic adaptation capabilities, and shared knowledge-construction behaviors. Research in Hungarian higher education contexts provides compelling evidence for this partnership phenomenon, with studies revealing that students primarily use AI systems for collaborative tasks such as brainstorming, information exploration, and iterative problem-solving rather than simple tool operation (Folmeg et al., 2024). I propose the Collaborative Learning Partnership Model as a theoretical framework that reconceptualizes LLMs as active learning agents rather than passive educational instruments. Drawing from systematic analyses of recent implementation research across multiple educational domains, my model identifies four core components: reciprocal agency, dynamic contextual adaptation, shared knowledge construction, and transparent collaboration protocols. This framework addresses challenges in AI integration, including academic integrity concerns, assessment innovation, and pedagogical role transformation. The model provides a theoretical foundation for effective LLM integration while maintaining educational rigor and human agency in learning processes. Furthermore, I

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present a four-stage partnership development progression that guides practical implementation strategies.

KEYWORDS: artificial intelligence, educational technology, collaborative learning, higher education, large language models, theoretical framework

JEL CODES: I23, O33, I21

1. Introduction

The integration of Large Language Models (LLMs) into higher education represents a paradigm shift in knowledge creation, distribution, and evaluation processes. Unlike previous educational technologies, LLMs such as ChatGPT and Claude demonstrate capabilities that extend beyond traditional tool functionality, engaging in dynamic, contextual interactions that mirror collaborative learning partnerships rather than passive instrument use.

Current educational technology frameworks remain anchored in tool-based paradigms that conceptualize technology as an external aid to human learning processes. The Technology Pedagogy Content Knowledge (TPACK) framework treats technology as one component in a triad of teacher knowledge domains (Mishra & Koehler 2006). Constructivist approaches assume that human agents are the primary drivers of knowledge construction. Even connectivist theories, while acknowledging networked learning, position technology as a medium rather than an active participant in learning ecosystems (Siemens 2005). This conceptual mismatch creates tensions in educational practice. These tensions are not abstract: the classroom reality between 2023 and 2025 was characterized by rapid, largely unguided student adoption. In a Hungarian pilot study, 68% of business students used ChatGPT for exam preparation, around half used it for writing tasks and grammar explanations, and 70% adopted the tool, although fewer received any explicit instruction in its use (Kétyi et al. 2024) we examined the potential benefits and opportunities that ChatGPT can bring to higher education, particularly from the perspective of business students and educators. The study included 41 participants and aimed to explore their opinions on using ChatGPT in business language classes. Twelve students did not use ChatGPT during the course (control group. Most students thus currently engage LLMs for quick instrumental tasks, summarizing lengthy readings, correcting grammar, and preparing for assessments, while institutions oscillate between prohibition and uncritical adoption (Niraula 2024). The model proposed in this paper starts from precisely this point: it offers the theoretical grounding needed to move from improvised, tool-like usage towards pedagogically productive collaboration.

Systematic literature analysis reveals LLMs consistently function as interactive partners rather than passive tools. Studies demonstrate that LLMs require iterative collaboration in programming contexts and participate in chain-of-thought reasoning processes that emerge through human-AI dialogue (Lee et al. 2024) but idea quality can be suboptimal, affected by a lack of resources or diversity of ideas. The use of generative Artificial Intelligence and large language models (LLMs. Hungarian higher education research corroborates this partnership phenomenon, with students primarily using AI systems for brainstorming, information exploration, and iterative problem-solving rather than simple tool operation (Folmeg et al. 2024). These patterns suggest relationships that traditional educational technology frameworks cannot accommodate, as LLM capabilities transcend simple responsiveness to exhibit characteristics typically associated with learning partners.

The problem extends beyond theoretical inadequacy to practical implementation challenges. When educators approach LLM integration through tool-based frameworks, they encounter issues with academic integrity, assessment validity, and pedagogical effectiveness. Students struggle to understand appropriate AI collaboration boundaries, while institutions develop policies that either prohibit or uncritically embrace LLMs without a clear theoretical grounding for their effective integration.

This paper proposes a theoretical reconceptualization of LLMs in higher education based on collaborative learning partnerships rather than educational tool paradigms. Drawing from systematic analyses of current implementation research and educational theory, I argue that LLMs exhibit characteristics of learning partners: reciprocal agency, dynamic interaction patterns, shared knowledge-construction capabilities, and contextual adaptation behaviors. This partnership model provides a more accurate theoretical foundation for understanding LLM integration while offering practical guidance for educators, students, and institutions navigating technological transformation.

2. Established frameworks encounter new challenges in the generative AI era

2.1. Technology integration frameworks are challenged by unprecedented capabilities

Established frameworks like TPACK have provided valuable foundations for understanding digital tool integration, positioning technology as one knowledge domain that teachers must master alongside pedagogical and content knowl-

edge (Mishra & Koehler 2006). Traditional educational technologies typically require human operation and direction: learning management systems store instructor-organized content, presentation software displays educator-created materials, and assessment tools apply predetermined criteria.

LLMs appear to demonstrate capabilities extending beyond this paradigm, actively contributing content, suggesting alternative approaches, and adapting responses based on contextual understanding. When students engage with generative AI to analyze literary texts, these systems seem to generate novel interpretations, pose clarifying questions, and provide feedback that builds upon existing understanding rather than simply retrieving stored information. This suggests interaction patterns that may require theoretical consideration beyond TPACK's original conceptualization.

Similarly, SAMR models assume predictable progression from basic tool use to transformational applications, yet LLMs appear to operate simultaneously at multiple functional levels within a single interaction, providing research assistance, brainstorming support, and process guidance while potentially altering fundamental assumptions about authorship itself. Both frameworks assume human agency in determining technology's role, whereas LLMs actively participate in determining their educational function through adaptive responses, representing a departure from tool-based paradigms that existing frameworks may struggle to accommodate.

2.2. Learning theories encounter new forms of collaboration

Constructivist theories have provided foundational insights into learner agency and knowledge building. Vygotsky's zone of proximal development conceptualizes learning through interaction with more capable peers, providing scaffolding (Vygotsky 1978), while Piaget's cognitive constructivism emphasizes individual knowledge construction through environmental interaction and cognitive conflict resolution (Piaget 1977). Traditional applications appropriately position digital tools as environmental elements that learners manipulate to construct knowledge.

Recent research suggests LLMs may present forms of interaction that extend beyond traditional constructivist assumptions while remaining consistent with constructivist principles. Dental education studies indicate that LLMs provide adaptive scaffolding, adjusting to student responses in real-time, demonstrating characteristics resembling human tutors (Claman & Sezgin 2024). Programming students report that AI systems provide scaffolding that adapts to their skill levels, offer increasingly sophisticated challenges, and model problem-solving approaches, resembling expert mentors. While differing from tra-

ditional human-human scaffolding, these interactions may suggest possibilities for extending constructivist frameworks to encompass new forms of collaborative knowledge construction.

Evidence from AI-generated medical case studies suggests learning outcomes may emerge from human-AI interaction in ways that complement rather than replace traditional constructivist processes, with knowledge representing collaborative construction building on constructivist principles while potentially requiring additional theoretical frameworks (Berbenyuk et al. 2024).

2.3. Network and social learning theories are challenged by new forms of participation

Siemens' connectivism has provided insights into learning in digital networks, recognizing knowledge as existing in connections between nodes rather than within individual minds (Siemens 2005). The theory's core principles—that learning is grounded in a diversity of opinions, involves connecting specialized sources, may reside in non-human appliances, and emphasizes the capacity to know over current knowledge—have contributed to understanding networked learning as more compatible with technological integration than traditional theories.

However, connectivism primarily addresses human learning through technological networks rather than accounting for AI agents that might actively participate in knowledge creation. Downes' refinement, which emphasizes the knowledge emerging from network connections, provides helpful foundations for contemporary learning environments (Downes 2012), yet recent evidence suggests LLMs may function as active network participants rather than passive connection facilitators. Chain-of-thought studies indicate that LLMs engage in collaborative reasoning, generating new insights through interaction and demonstrating behaviors that adapt based on student input (Lee et al. 2024). Programming education research suggests that LLMs function as network participants, contributing unexpected solutions and adaptive scaffolding rather than simply connecting learners to information sources (Gao et al. 2023).

Bandura's social learning theory, which emphasizes learning through observation, imitation, and modeling (Bandura 1977), faces similar challenges. While traditionally applied to human-human observational learning, LLM interactions appear to involve reciprocal modeling relationships where AI systems adapt their modeling based on student responses and needs. Students seem to observe and model AI analytical approaches while AI systems provide increasingly sophisticated reasoning examples, suggesting interactions that may extend traditional social learning theory's model-observer conceptualization.

2.4. Academic integrity frameworks face fundamental complexities

Traditional academic integrity frameworks appropriately distinguish between acceptable resources and assistance that might compromise individual assessment, with technology serving as a tool for either legitimate assistance or unauthorized aid. Plagiarism detection systems and assessment protocols designed around human-authored content position technological tools as secondary forms of support.

LLM capabilities present complexities that these frameworks were not designed to address. Research revealing AI-generated content as nearly indistinguishable from student work creates conceptual rather than technological detection challenges: existing frameworks struggle to categorize human-AI collaborative products within traditional categories of individual work, collaboration, or tool-assisted completion (Ülkü 2023).

Consider students who use ChatGPT to analyze historical documents—the AI might suggest analytical frameworks, raise contextual questions, propose alternative interpretations, and help organize arguments. The resulting analysis emerges from human-AI interaction, in which both contribute intellectual content. Traditional integrity frameworks find it challenging to categorize this as legitimate tool use, unauthorized assistance, or acceptable collaboration, primarily because these categories assume clearer distinctions between human agency and technological support than current AI capabilities may allow.

Assessment protocols designed around human-authored content encounter challenges when students collaborate with AI systems. Traditional evaluation focuses on individual knowledge demonstration, critical thinking, and content mastery, yet student-AI collaboration may produce syntheses that existing assessment approaches were not designed to evaluate comprehensively. Institutional responses reveal understandable uncertainty, with universities oscillating between prohibition and permissive policies without clear precedents for distinguishing appropriate from inappropriate AI collaboration (Niraula 2024).

Hungarian higher education policy provides relevant context, as government initiatives now require universities to comprehensively review internal AI regulations by September 2025, explicitly recognizing the need for new policy frameworks to guide integration efforts. These developments suggest opportunities to develop complementary theoretical approaches that accommodate collaborative learning while maintaining educational standards and meaningful learning evaluation.

3. The collaborative learning partnership model

This section first describes the analytical approach and theoretical foundations on which the model rests, then defines its key terminology, presents its four core components, and finally introduces a four-stage progression of partnership development. Together, these elements provide both the conceptual justification for the partnership perspective and the operational vocabulary used in the remainder of the paper.

Concerning the method, the model was developed through a systematic qualitative analysis of recent implementation research rather than through new empirical data collection. Peer-reviewed studies published between 2022 and 2024 were identified in Scopus and Google Scholar using combinations of the terms “large language model,” “ChatGPT,” “higher education,” “collaboration,” and “learning,” and were retained if they reported interaction-level evidence of LLM behavior in authentic educational settings. The resulting corpus spans multiple domains: programming, medical, dental, language, and tourism education, complemented by Hungarian higher education studies and foundational learning theory. These sources were analyzed through iterative thematic synthesis: recurring interaction patterns that existing tool-based frameworks could not accommodate were coded and progressively condensed into the four core components presented in Section 3.2.

3.1. Theoretical foundation

I propose the Collaborative Learning Partnership Model as a theoretical reconceptualization that addresses fundamental challenges in existing educational technology frameworks when applied to LLM integration. This model conceptualizes LLMs as active learning agents that engage in reciprocal knowledge construction with human learners rather than as sophisticated educational tools. The framework draws from partnership learning theory, which emphasizes mutual contribution, shared responsibility, and collaborative meaning-making between participants with complementary capabilities (Barkley et al. 2014), though I extend this framework beyond traditional human-human partnerships to encompass human-AI collaborative relationships.

Partnership learning theory emerged from the recognition that effective collaboration requires more than simple cooperation or coordination. True partnerships involve reciprocal contributions, in which each participant brings distinct capabilities that enhance collective performance beyond what any individual could achieve independently. Traditional partnership learning focuses on complementary human skills—analytical and creative thinking, different knowl-

edge domains, varied cultural perspectives—that combine to produce superior learning outcomes.

The theoretical foundation for extending partnership concepts to human-AI collaboration rests on several key insights from cognitive science and learning theory. First, distributed cognition research demonstrates that thinking and problem-solving often occur across multiple agents and artifacts rather than within individual minds (Hutchins 1995). Second, situated learning theory emphasizes how learning emerges from interaction between learners and their environment, including both human and non-human elements (Lave & Wenger 1991). Third, activity theory provides frameworks for understanding how learning occurs through collaboration between agents with different but complementary capabilities (Engeström 1987).

Unlike tool-based models that position technology as an external instrument, or network models that treat AI as infrastructure, my partnership model recognizes LLMs as entities capable of contributing distinct forms of agency to learning processes. This agency is not equivalent to human consciousness but represents genuine responsiveness, adaptation, and a contribution to knowledge construction that exceeds traditional technological functionality. I acknowledge that AI agency differs qualitatively from human agency while recognizing that these differences can enable productive complementary collaboration.

To avoid potential confusion, the key terms of the model are defined as follows. Agency denotes the capacity to influence the direction and content of a learning interaction; AI agency is functional rather than phenomenal; it consists of pattern-based responsiveness, adaptation, and contribution, without consciousness, intentions, lived experience, or moral accountability, all of which remain exclusively human. Human agency, by contrast, includes goal-setting, value judgment, and responsibility for outcomes, and the model preserves its primacy throughout. Partnership refers to a structured collaborative relationship between participants with complementary capabilities; it implies reciprocal contribution but not equality of moral or epistemic status. Collaboration designates the concrete interactional process—the iterative exchange through which contributions of both parties are combined.

Furthermore, my partnership model draws from theories of cognitive complementarity that suggest effective problem-solving often requires the combination of different types of thinking processes (Kahneman 2011). Human cognition excels at intuitive understanding, creative insight, contextual interpretation, and value-based reasoning. AI systems demonstrate strengths in pattern recognition, systematic analysis, rapid information processing, and the consistent application of logical frameworks. My partnership model proposes that educational collaboration can leverage these complementary cognitive capabilities to enhance learning outcomes while maintaining human agency in learning pro-

cesses. Hungarian research on smart education implementation provides empirical support for this cognitive complementarity approach, demonstrating how digital technologies can effectively augment human learning capabilities when properly integrated into educational frameworks (G. Molnár & Csapó 2023).

3.2. Core components of the partnership model

I identify four components that distinguish partnership-based from tool-based AI integration. Each component addresses specific limitations in current educational technology theory while providing operational guidance for implementation. Figure 1 summarizes the model: the four core components jointly constitute the partnership relationship, which learners enter and deepen through the four developmental stages described in Section 3.3.

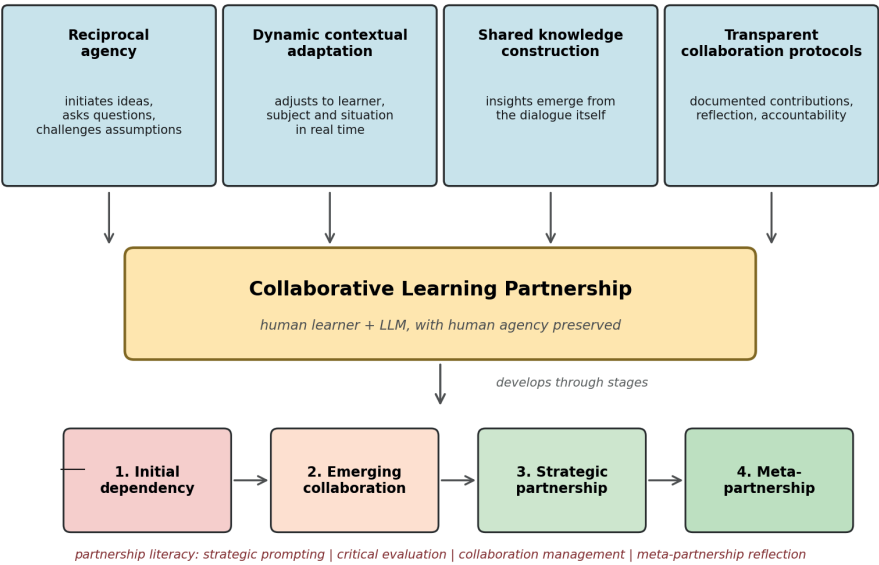


Figure 1. The Collaborative Learning Partnership Model: four core components constituting the partnership, and the four-stage development progression.

Source: author.

3.2.1. Reciprocal agency: beyond responsive functionality

Traditional educational technology exhibits responsive functionality: i.e., reacts to user input according to programmed parameters. LLMs demonstrate reciprocal agency through their capacity to contribute unexpected perspectives, ask clarifying questions, and introduce novel elements to learning interactions rather than simply responding to human queries. This agency manifests as the ability to initiate ideas, challenge assumptions, and guide collaborative directions.

Hungarian research that has examined students' AI collaboration patterns found that learners reported AI contributions often surprised them and led to deeper analysis than they would have achieved independently, with participants describing collaborative processes that exceeded simple tool usage (Folmeg et al. 2024). This represents genuine reciprocal contribution rather than sophisticated tool responsiveness. The reciprocal nature of AI agency becomes particularly evident in programming education contexts.

Program-Aided Language Model research demonstrates LLMs contributing distinct problem-solving approaches that complement human conceptual thinking with computational precision (Gao et al. 2023). The partnership produced solutions that neither human logical reasoning nor computational processing could achieve independently—a hallmark of reciprocal agency. Students learned to structure problems in ways that leveraged AI computational capabilities while AI systems adapted their analysis to human conceptual frameworks.

Reciprocal agency also manifests in LLMs' capacity to initiate questions and request clarification that advances learning objectives. AI systems actively probe student understanding, identify gaps in reasoning, and suggest areas for deeper exploration. Medical education research demonstrates that AI systems ask clarifying questions about case presentations, helping students recognize important diagnostic considerations they might otherwise overlook (Berbenyuk et al. 2024). This questioning behavior differs qualitatively from programmed prompts or predetermined decision trees because it emerges from AI interpretation of collaborative dynamics rather than pre-scripted educational sequences. In plain terms: the AI does not merely answer; it also asks, suggests, and sometimes surprises, and learning benefits from this two-way dynamic.

3.2.2 Dynamic contextual adaptation: multi-dimensional responsiveness

Traditional educational tools maintain consistent functionality across contexts. LLMs exhibit dynamic adaptation that adjusts interaction patterns based on learner characteristics, subject matter, and situational factors. This adaptation

occurs in real time through ongoing interaction rather than through preconfigured settings, representing sophisticated contextual understanding that enables responsive pedagogical support.

LLMs provide different levels of scaffolding and explanation based on student responses, gradually adjusting complexity and detail to match learner needs (Karabacak et al. 2023). The AI systems examined by the latter demonstrated awareness of student confusion or understanding and modified their teaching approach accordingly. This contextual sensitivity resembles effective human tutoring more than the operation of a technological tool. The adaptation process involves multiple simultaneous adjustments: content complexity, explanation detail, questioning strategies, examples and analogies, interaction pacing, and scaffolding intensity. Students working with AI systems in mathematics education report that systems gradually increase problem difficulty as competence demonstrates, provide additional explanation when confusion becomes apparent, and offer alternative solution approaches when initial methods prove ineffective (Yadav et al. 2016). This represents partnership-like responsiveness to collaborative dynamics rather than predetermined educational sequences. Hungarian research on technology-based assessment reveals similar adaptive patterns, with digital systems demonstrating sophisticated contextual responsiveness that adjusts to learner characteristics and performance patterns in real time (Csapó & Molnár 2019).

LLMs adjusted their feedback complexity based on student skill level and provided increasingly sophisticated analyses as students demonstrated readiness for advanced concepts (Claman & Sezgin 2024). This adaptation emerged through interaction rather than explicit programming, suggesting partnership-like responsiveness to collaborative dynamics.

Domain-specific adaptation represents another dimension of contextual responsiveness. LLMs demonstrate the ability to adjust their analytical frameworks, terminology, and reasoning approaches based on disciplinary context. The same AI system provides different types of support for creative writing versus mathematical problem-solving versus analytical reasoning, adapting not only content but also pedagogical strategies to match disciplinary learning objectives (Gao et al. 2023). This sophisticated domain adaptation exceeds traditional tool functionality and suggests genuine contextual understanding. The meaning of partnership itself varies accordingly across disciplines: in a creative writing course the model functions mainly as a muse, offering variations and provocations for the student to react against, whereas in a physics course it acts more as a tutor or calculator whose outputs must be checked against established methods; the assessment of collaboration quality therefore needs to be calibrated to disciplinary norms. In plain terms: the same system behaves differently with different students, subjects, and moments much as a good tutor would.

3.2.3. *Shared knowledge construction: collaborative epistemology*

Traditional learning models assume human agents construct knowledge using technological tools for information access or processing support. My partnership model recognizes that knowledge emerges from human-AI interaction itself, representing genuine collaborative construction that neither party could achieve independently. This shared construction process involves iterative dialogue, mutual influence, and synthetic outcomes that combine human insight with AI analysis.

Chain-of-thought research provides compelling evidence for shared knowledge construction across multiple reasoning tasks. Students working with LLMs on complex reasoning problems produced insights that emerged from iterative dialogue between human intuition and AI analysis (Lee et al. 2024). The knowledge created was neither purely human reasoning nor AI-generated content but represented a genuine synthesis that required both types of cognitive contribution. This collaborative epistemology challenges traditional assumptions about individual knowledge construction.

The collaborative construction process typically involves several phases: initial problem exploration, where both human and AI contribute perspectives; iterative refinement, where each party builds upon the other's contributions; synthesis generation, where combined insights produce a new understanding; and validation, where collaborative outcomes are evaluated and refined. This process differs from traditional tool use where humans operate technology to achieve predetermined objectives. AI-generated clinical scenarios prompted student analysis and discussion that produced diagnostic insights not present in either original AI content or student prior knowledge (Berbenyuk et al. 2024).

Programming education provides particularly clear examples of shared knowledge construction where human problem-solving intuition combines with AI's computational capabilities to produce solutions that neither could generate independently. Students report learning new programming concepts through AI collaboration that they could not have discovered through traditional instruction or independent practice (Gao et al. 2023). Furthermore, this collaborative construction extends beyond simple question-answering or information retrieval to encompass genuine intellectual partnership. Large-scale empirical studies in Hungarian higher education contexts reveal significant patterns in collaborative AI usage, with students across different fields demonstrating the sophisticated integration of AI insights with their own analytical processes (Folmeg et al. 2024). In plain terms: some of what a student ends up knowing is produced through the conversation itself—neither party brought it in ready-made.

3.2.4. *Transparent collaboration protocols: accountability framework*

My partnership model requires an explicit acknowledgment of AI collaboration and a mutual understanding of respective contributions. Unlike tool usage, which may be invisible or secondary to primary work, partnership collaboration should be transparent and integral to learning processes. Transparency enables the appropriate evaluation of learning outcomes while maintaining academic integrity within the partnership paradigm.

Institutional policy analysis reveals widespread confusion about appropriate AI collaboration precisely because current frameworks lack protocols for transparent partnership (Niraula 2024). Students and educators struggle to distinguish between legitimate collaboration and inappropriate dependency because tool-based frameworks provide no guidance for managing partnership relationships. My partnership model addresses this confusion by establishing clear expectations for collaborative transparency.

Transparent collaboration involves several interconnected elements that distinguish partnership from dependency or deception. First, explicit acknowledgment requires clear documentation of AI collaboration, including the nature of AI contributions, the extent of collaborative interaction, and the student's role in guiding and evaluating the partnership. This acknowledgment differs from simple citation because it describes the collaborative process rather than source attribution.

Second, contribution documentation involves a detailed analysis of respective human and AI contributions to collaborative outcomes. Students must articulate their intellectual contribution to partnership products, including problem framing, critical evaluation, synthesis decisions, and application insights. This documentation enables an assessment of student learning while acknowledging AI collaboration.

Third, process reflection requires students to analyze partnership dynamics, collaboration effectiveness, and learning outcomes. Students evaluate the quality of their AI collaboration, identify areas for improvement, and demonstrate understanding of appropriate partnership boundaries. This reflection develops partnership literacy while providing evidence of learning process engagement.

Fourth, collaborative decision-making involves explicit student choices about when and how to engage in an AI partnership, based on learning objectives and contextual factors. Students must demonstrate strategic thinking about AI collaboration rather than reflexive dependence or automatic usage. This decision-making capability represents crucial partnership literacy that enables effective long-term collaboration.

Transparency protocols also include clear guidelines for collaboration boundaries that help students and educators distinguish between appropriate

partnership and problematic dependency. These boundaries consider learning objectives, assessment requirements, disciplinary norms, and institutional policies while providing flexibility for legitimate educational collaboration. Furthermore, assessment integration represents a crucial aspect of transparent collaboration where evaluation approaches acknowledge and assess partnership outcomes rather than attempting to isolate human contributions. In plain terms: students should show how they worked with the AI, not hide that they did.

3.3. Partnership development stages

My partnership model recognizes that effective human-AI collaboration requires skill development along several dimensions. Based on patterns identified in implementation research and learning theory, partnership development progresses through identifiable stages that represent increasing sophistication in collaborative capabilities and understanding.

3.3.1. *Initial dependency stage: passive consumption*

Learners in the initial dependency stage rely heavily on AI output without critical evaluation or strategic interaction. This stage resembles traditional tool usage where students treat AI systems as sophisticated information sources or automated task-completion services. Collaboration lacks reciprocal interaction, critical evaluation, or the strategic deployment of AI capabilities.

Programming education research documents characteristics of dependency-stage collaboration that produce negative learning outcomes. Students copy AI-generated code without understanding the underlying logic, accept AI solutions without verification, and fail to develop independent problem-solving capabilities (Jošt et al. 2024). This stage represents problematic collaboration that undermines rather than enhances learning objectives.

Dependency behaviors include a passive acceptance of AI output, minimal human intellectual contribution, single-interaction usage patterns, concealment of AI collaboration, and failure to develop critical evaluation skills. Students at this stage often struggle to explain AI-generated content, cannot identify errors or limitations in AI output, and become increasingly reliant on AI assistance for basic tasks. Educational interventions at this stage focus on developing critical evaluation skills, encouraging iterative interaction, and establishing appropriate collaboration boundaries.

3.3.2. Emerging collaboration stage: skill development

Learners begin developing prompting skills and critical evaluation capabilities as they progress to the emerging collaboration stage. They start to engage in iterative interaction with AI systems and recognize the importance of human guidance in partnership. This stage represents a transition from passive consumption to active collaboration.

Research on AI collaboration illustrates students developing collaboration capabilities through structured practice and feedback. Students learn to formulate effective queries, interpret AI responses critically, and engage in multi-turn dialogues that refine understanding and improve outcomes. This development requires practice and guidance rather than occurring automatically. Hungarian research on adaptive pedagogical strategies provides important context for this developmental process, revealing that successful technology integration requires flexible approaches and enhanced feedback mechanisms that support student engagement in digital learning environments (Horvath 2023).

Emerging collaboration characteristics include strategic questioning, iterative refinement of AI interactions, basic critical evaluation of AI output, growing awareness of AI limitations, and increased confidence in guiding collaborative interactions. Students begin to understand how their input affects AI responses and develop strategies for optimizing collaborative effectiveness. Educational support at this stage involves guided practice with AI collaboration, structured reflection on partnership dynamics, peer collaboration that enables observation of effective strategies, and explicit instruction in collaboration optimization techniques.

3.3.3. Strategic partnership stage: advanced collaboration

Learners demonstrate sophisticated partnership management skills, including effective prompting, critical evaluation of AI contributions, and strategic deployment of AI capabilities for specific learning goals. They understand the respective strengths and limitations of human and AI participants and can optimize collaboration for different tasks and contexts.

Research across various educational domains demonstrates the characteristics of strategic partnerships, including the contextual adaptation of collaboration strategies, a sophisticated understanding of AI capabilities and limitations, the effective integration of AI insights with human analysis, and strategic decision-making about when to engage an AI partnership versus independent work. Students at this stage can articulate rationales for their collaboration choices, demonstrate effective strategies for different types of AI interaction, critically evaluate and improve upon AI output, and teach partnership skills to others.

Furthermore, learners view AI collaboration as one tool among many for achieving learning objectives rather than as a default approach to all tasks. Educational development at this stage focuses on advanced collaboration techniques, exposure to diverse AI applications across domains, opportunities to mentor less experienced students, and reflection on optimizing partnership approaches for different learning contexts. Hungarian research on teacher digital competence development provides valuable insights into this advanced stage, demonstrating that sophisticated technology integration requires systematic self-reflection and institutional support that enables educators to develop advanced partnership facilitation capabilities (Horvath et al. 2020; Horváth et al. 2025).

3.3.4. Meta-partnership stage: expertise and teaching

Learners can reflect on and optimize partnership dynamics, teach partnership skills to others, and adapt collaboration strategies for different contexts and objectives. They view AI collaboration as an integral aspect of their learning and professional practice while maintaining an appropriate critical perspective on AI's capabilities and limitations.

Meta-partnership capabilities include the systematic evaluation of collaboration effectiveness, the strategic adaptation of partnership approaches across different domains and contexts, mentoring of others in partnership development, and contributing to the development of best practices for human-AI collaboration in educational and professional contexts. Students at this stage often become resources for institutional policy development, peer education about effective AI collaboration, and research into the optimization of human-AI partnerships in educational contexts. Moreover, learners demonstrate a sophisticated understanding of ethical considerations, cultural variations in AI collaboration, and the long-term implications of human-AI partnerships for learning and professional development. Educational opportunities at this stage include leadership roles in peer education, participation in research on AI collaboration, contributions to policy development, and advanced exploration of cutting-edge AI applications within their disciplinary domains.

4. Implications for pedagogical practice

This section translates the model into practice along four lines: the transformation of instructor roles (4.1), the partnership-literacy competencies students must develop (4.2), the redesign of assessment and academic integrity (4.3), and institutional implementation strategies (4.4).

4.1. Transforming instructor roles: from delivery to facilitation

My partnership model fundamentally alters instructor roles from information delivery and skill transmission to partnership facilitation and collaboration coaching. Rather than competing with AI capabilities or restricting AI access, educators become guides who help students develop effective human-AI collaborative relationships.

Research provides evidence for this role transformation across multiple educational contexts. In Education 4.0 studies, successful LLM integration required instructors who could facilitate AI-human collaboration rather than traditional content delivery (Peláez-Sánchez et al. 2024). Educators reported their most valuable contributions involved helping students develop critical evaluation skills, strategic prompting capabilities, and reflective partnership practices rather than providing information that AI systems could readily supply. Hungarian research on technology integration reveals that successful classroom technology adoption requires educators functioning as facilitators of collaborative learning rather than traditional content deliverers (P. Molnár et al. 2011).

This transformation requires new instructor competencies extending beyond traditional technological literacy or pedagogical content knowledge. Partnership literacy involves understanding AI capabilities and limitations, effective collaboration strategies, and appropriate partnership boundaries within specific disciplinary contexts. Facilitation skills involve guiding students through partnership development stages, providing feedback on collaboration quality, and helping students troubleshoot partnership challenges. Assessment innovation involves developing evaluation approaches that measure partnership outcomes rather than individual performance while maintaining educational rigor.

Language education research provides specific examples of transformed instructor roles. English as a foreign language teachers report shifting from grammar instruction and vocabulary drilling to facilitating student collaboration with AI conversation partners and writing assistants (Albadarneh et al. 2024). Instructors focus on helping students develop strategic interaction skills, cultural awareness in AI communication, and the ability to critically evaluate AI language support rather than traditional language instruction activities.

4.2. Developing student partnership literacy: essential competencies

Partnership literacy requires competencies specific to AI collaboration that represent new forms of learning skills essential for effective educational and profes-

sional practice in AI-integrated environments. I identify four core competency areas students must develop for effective human-AI collaboration.

Strategic prompting involves understanding how to structure queries and interactions to maximize AI contributions while maintaining human intellectual engagement. Research shows this skill develops through practice with feedback rather than explicit instruction alone. Strategic prompting includes understanding AI response patterns, formulating clear objectives, providing appropriate context, and iterating based on AI output quality. Programming education demonstrates the complexity of strategic prompting skills, where students must learn to decompose problems into components suitable for AI assistance, provide sufficient context, evaluate AI suggestions for correctness, and integrate AI contributions with their own problem-solving approaches (Gao et al. 2023).

Critical evaluation involves assessing AI output for accuracy, bias, relevance, and completeness, extending beyond traditional source evaluation to understanding AI-specific limitations and strengths. Hungarian studies examining AI literacy development found students initially struggled with critical evaluation but developed sophisticated assessment capabilities through structured collaborative experiences (Folmeg et al. 2024). Medical education research highlights the importance of critical evaluation when students work with AI diagnostic tools, requiring the evaluation of AI suggestions against clinical evidence and the integration of AI insights with human clinical reasoning (Berbenyuk et al. 2024).

Collaboration management involves recognizing when AI partnership is beneficial versus when independent human thinking is preferable, understanding how to sequence AI collaboration within broader learning processes, and maintaining intellectual responsibility for collaborative outcomes. Tourism education research revealed that effective students learned to use AI for specific purposes while maintaining overall intellectual ownership of their work (Ülkü 2023).

Meta-partnership reflection involves developing awareness of partnership dynamics, monitoring collaboration quality, and adjusting partnership strategies based on learning goals and outcomes. This metacognitive dimension enables continuous improvement in the effectiveness of collaboration and the transfer of partnership skills across different contexts and domains.

4.3. Reimagining assessment and academic integrity within partnership frameworks

Traditional assessment assumes individual human authorship and measures isolated performance on specific tasks. My partnership model requires assessment innovation that evaluates collaborative outcomes while maintaining academic rigor and the meaningful evaluation of student learning.

Assessment innovation involves multiple interconnected changes in evaluation philosophy, criteria, and methodology. Process-focused assessment includes documentation and evaluation of partnership processes rather than evaluating only final products. Students might submit collaboration logs detailing their interaction strategies, decision-making processes, and reflection on partnership effectiveness. Process documentation might include transcripts of AI interactions with student annotations, reflection essays analyzing partnership decisions, evidence of iterative refinement in collaboration strategies, and demonstration of strategic thinking about AI partnership deployment.

Collaboration quality metrics involve assessment criteria that evaluate the effectiveness of human-AI collaboration rather than attempting to isolate human contributions. Quality metrics focus on how well students manage collaborative relationships, including the clarity and strategic nature of student prompting, evidence of critical evaluation and validation of AI output, the sophistication of integration between AI insights and student reasoning, and the appropriateness of collaboration decisions for specific learning objectives. Medical education research provides examples of when students are evaluated on their ability to integrate AI diagnostic suggestions with clinical reasoning rather than on independent diagnostic capability alone (Karabacak et al. 2023). Table 1 operationalizes these criteria as a sample rubric that instructors can adapt to disciplinary contexts.

Table 1. Sample rubric for assessing the quality of human-AI collaboration.

Criterion	Developing	Proficient	Advanced
Strategic prompting	Single, vague queries; accepts first output	Provides context and objectives; iterates on responses	Decomposes problems strategically; adapts prompting to task and discipline
Critical evaluation	Takes AI output at face value	Verifies key claims; identifies obvious errors or bias	Systematically validates against sources; articulates AI-specific limitations
Integration and synthesis	Copies AI content with minimal own contribution	Combines AI input with own reasoning in identifiable ways	Produces synthesis exceeding either contribution; can explain each party's role
Collaboration decisions	Uses AI reflexively for all tasks	Distinguishes tasks where AI helps from those requiring independent work	Justifies collaboration choices in relation to learning objectives
Transparency and reflection	Conceals or vaguely reports AI use	Documents AI contributions and own role accurately	Reflects critically on partnership dynamics and improves strategies over time

Source: author.

Academic integrity is reframed from individual authorship to transparent collaboration. Rather than asking whether AI usage constitutes cheating, the framework focuses on collaboration quality and transparency while maintaining educational standards. Transparent attribution involves students acknowledging AI collaboration explicitly and documenting their respective contributions, going beyond simple citation to include an analysis of collaborative dynamics and individual contributions to partnership outcomes. Tourism education research demonstrates the complexity of attribution in collaborative contexts where AI systems contribute ideas, analysis, and writing support that becomes integrated with student thinking (Ülkü 2023).

Partnership ethics involves students developing an understanding of appropriate collaboration boundaries, including when AI partnership is suitable versus when independent work is required. This ethical framework extends beyond rule compliance to the development of professional judgment that prepares students for complex decisions about AI collaboration in their careers.

4.4. Institutional implementation strategies: systematic change management

Successful implementation requires coordinated institutional efforts that address policy development, faculty preparation, infrastructure development, and cultural change management. Research demonstrates that ad hoc approaches to AI integration often produce unsatisfactory outcomes, while comprehensive institutional strategies enable more effective implementation.

Policy development involves institutions developing coherent policies that provide clear guidance for partnership-based education while maintaining flexibility regarding disciplinary differences and evolving technological capabilities. Effective policies provide clear expectations for transparent collaboration, guidelines for appropriate partnership boundaries in different contexts, support for faculty development and student education about partnership skills, and mechanisms for the ongoing evaluation and adjustment of partnership approaches.

Faculty development involves comprehensive programs that help educators understand partnership concepts, develop collaboration facilitation skills, and adapt teaching practices for AI-integrated environments. Professional development programs might include workshops on partnership literacy and facilitation skills, opportunities for faculty to experience AI collaboration in their own research and professional practice, the collaborative development of discipline-specific partnership guidelines, and ongoing support for innovation in partnership-based pedagogy.

Infrastructure development requires appropriate technological infrastructure, policy frameworks, and support systems. Infrastructure considerations include access to appropriate AI systems for educational use, technical support for faculty and students using AI tools, privacy and security protections for educational AI use, and the integration of AI tools with existing educational technology systems.

Cultural change management involves implementing partnership-based education as cultural change in educational institutions. Success requires intentional change management that addresses resistance, builds understanding, and creates supportive environments for innovation while maintaining educational quality and institutional values. Hungarian institutional experiences provide valuable context, as universities simultaneously launch AI-focused master's programs with coordinated curricula while grappling with policy development challenges that reflect broader theoretical confusion about AI's educational role.

5. Future directions and limitations

5.1. Research priorities

My Collaborative Learning Partnership Model requires empirical validation across several dimensions. Longitudinal studies should examine how partnership literacy develops over time and transfers across different learning contexts, providing evidence for the four-stage developmental progression I propose. Comparative research investigating partnership-based versus tool-based implementation approaches would demonstrate the model's practical effectiveness through learning outcomes, student satisfaction, and academic integrity measures.

Cross-disciplinary research must explore how partnership dynamics vary across different fields, as programming education partnership needs likely differ from creative writing or clinical medicine contexts. Additionally, institutional implementation studies that examine different policy approaches could reveal effective change management strategies and identify scalability constraints.

5.2. Key limitations

The framework may not apply equally across all educational contexts. Some learning situations may require purely human engagement, and current LLM limitations—including hallucination, bias, and inconsistency—may prevent genuine partnership in certain contexts. Cultural and linguistic factors may also influence partnership dynamics in ways requiring model adaptation.

5.3. Ethical and equity implications

Partnership-based AI integration raises significant concerns about educational equity. Students with greater AI access or partnership literacy may gain substantial advantages, potentially exacerbating existing inequalities. Implementation must address issues of AI bias, privacy, and data security within educational partnerships.

The long-term implications for human learning capabilities remain unclear. Research must examine whether extensive AI collaboration enhances or potentially diminishes human cognitive capabilities, critical thinking skills, and independent problem-solving abilities. Understanding these effects is crucial for designing approaches that leverage AI benefits while preserving essential human capacities.

The model must also consider labor market implications, ensuring that partnership-based education adequately prepares students for workplace AI integration challenges while maintaining a focus on developing human expertise that remains valuable in AI-augmented professional environments.

6. Conclusions

The Collaborative Learning Partnership Model provides a theoretical foundation for LLM integration in higher education that fundamentally reconceptualizes artificial intelligence as collaborative learning agents rather than educational tools. This shift addresses critical inadequacies in existing frameworks—TPACK, SAMR, constructivism, and connectivism—that cannot accommodate the complex, interactive, and adaptive behaviors LLMs demonstrate in educational contexts.

The model's four core components establish a comprehensive framework for human-AI collaborative learning: reciprocal agency recognizes that LLMs contribute unexpected perspectives that advance learning beyond individual capabilities; dynamic contextual adaptation acknowledges sophisticated responsiveness to learner characteristics and situational factors; shared knowledge construction recognizes learning outcomes emerging from collaborative interaction itself; and transparent collaboration protocols maintain academic integrity within partnership paradigms.

Partnership literacy represents the model's crucial practical contribution, identifying competencies essential for AI-integrated environments: strategic prompting, critical evaluation, collaboration management, and meta-partnership reflection. These extend beyond traditional digital literacy to encompass sophisticated collaborative dynamics and strategic AI deployment.

Implementation requires substantial transformation in educational practice. Instructors must evolve from information deliverers to partnership facilitators, developing new competencies in collaboration coaching. Assessment must move beyond individual authorship to evaluate partnership quality and collaborative processes. Academic integrity frameworks must evolve from prohibition-based to transparency-based approaches that maintain rigor while acknowledging collaborative realities.

The four-stage development model—from initial dependency through strategic partnership to meta-partnership—provides practical implementation guidance while recognizing that effective collaboration requires systematic skill development over time.

However, significant challenges remain. Anthropomorphic language may obscure important differences between human consciousness and AI computation. Cultural, contextual, and technological factors may require model adaptation. Equity concerns pose ongoing challenges, and partnership-based education could exacerbate educational inequalities without careful policy management.

Implementation demands sustained institutional commitment to faculty development, policy innovation, and resource investment. Success requires comprehensive change management that addresses resistance while maintaining educational quality and institutional values.

Despite these challenges, the partnership model provides an essential theoretical foundation for navigating the complex opportunities and challenges of LLM integration. As AI capabilities evolve rapidly, educational institutions require robust frameworks that accommodate technological advancement while preserving human agency and learning effectiveness.

The transformation from tool-based to partnership-based conceptualization represents a fundamental shift in understanding learning, knowledge construction, and educational relationships in AI-integrated contexts. By recognizing LLMs as collaborative partners, institutions can develop integration strategies that enhance, rather than replace, human learning while preparing students for careers in which AI collaboration is expected.

The core insight remains transformative: effective AI integration requires understanding LLMs as collaborative partners rather than instruments, with all the theoretical and practical implications such recognition entails. This partnership perspective provides evidence-based guidance for policy development and pedagogical innovation while addressing legitimate concerns about AI's educational impact.

The future of higher education lies not in choosing between human and artificial intelligence, but in developing a sophisticated understanding of how to collaboratively enhance human learning and development. This collaborative

future requires new theoretical frameworks, innovative approaches, and a sustained commitment to educational excellence that the partnership model supports and advances.

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