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AI across borders: COIL pedagogy, media ecology, and intercultural AI literacy in the postdigital classroom

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Abstract

Purpose: As AI becomes embedded in educational life worldwide, AI literacy can no longer be understood only as a technical competency. This article examines the cultural, linguistic, and ecological dimensions of AI use in higher education and argues that global communication classrooms require new pedagogical approaches for navigating AI across contexts of difference. Drawing on media ecological scholarship, we present a three-phase conceptual framework (Immersion, Encounter, Reflection) for developing Intercultural AI Literacy (ICAL).
Method: We report findings from "AI Across Borders," a Collaborative Online International Learning (COIL) exchange between undergraduate students at Penn State Behrend (United States) and Universidad Panamericana (Mexico City). Using quantitative survey analysis ($N = 150$; Penn State $n = 55$, UP Mexico $n = 95$), we examine similarities and differences in AI attitudes reported by US and Mexican students following participation in the exchange.
Findings: Composite-level analyses reveal similar post-exchange patterns in reported AI self-efficacy and cross-cultural orientation across both cohorts. Because the AI-in-higher-education item grouping demonstrated low internal consistency, it is interpreted cautiously as exploratory. Item-level analyses identify differences in reported prior AI educational exposure and default AI-use behavior. Equity-relevant subgroup analyses also suggest relationships between financial precarity and selected AI-literacy measures that warrant further study.

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Implications: AI literacy education requires intercultural and ecological reorientation. COIL pedagogy offers a productive site for developing ecological AI consciousness. Structural inequities in AI access must be integrated into curriculum design, not treated as demographic covariates.
Value: This study offers an initial cross-national empirical mapping of AI literacy attitudes across US and Mexican undergraduate contexts, advances Intercultural AI Literacy as a pedagogical concept, and argues for a media ecological approach to AI literacy that centers cultural difference, structural equity, and global communication.

Keywords: COIL; AI literacy; media ecology; intercultural communication; higher education; postdigital

1 Introduction

Artificial intelligence is not a monolithic entity but a heterogeneous assemblage of systems, techniques, and applications that operate at different levels of abstraction and social integration. In this article, we distinguish explicitly between generative AI systems – particularly large language models (LLMs), which produce text, images, and other content – and broader forms of AI, including predictive analytics, recommendation systems, and automated decision-making infrastructures. While generative AI has become the most visible interface for students in educational contexts, it represents only one layer of a wider AI ecology that shapes knowledge production and circulation.

We are living through what Luciano Floridi (2014) called the fourth epistemological revolution, a wholesale reorganization of how human beings understand themselves, their relationships, and their world through information and communication technologies. Artificial intelligence stands at the center of this transformation, and yet the discourse surrounding AI in higher education remains incomplete. It speaks often of capability and efficiency, occasionally of ethics, and rarely of culture. What AI literacy frameworks have not yet adequately asked (and what this paper argues must urgently be asked) is: whose AI is it, who is it made for, and what does it do beyond what it is intended to do?

Like technologies of the past, the tools, languages, and logics of artificial intelligence are not neutral (Petricini 2025). They emerge from specific cultural, economic, and linguistic contexts, carrying assumptions about what knowledge is valuable, what language is standard, and whose behavior is considered “normal”

(Benjamin 2019; Noble 2018; Petricini 2024). When students from different nations meet across an AI-mediated exchange, they do not merely encounter different opinions about technology. They encounter one another's entire media ecologies as the environments, habits, institutions, and narratives through which AI has entered their lives.

Marshall McLuhan (1964) insisted that the medium is the message. For him, the form a technology takes shapes perception more fundamentally than the content it carries. This insight applies with particular force to artificial intelligence, which functions not merely as a tool but as an extension of human cognition that operates largely invisibly, shaping the environments in which we learn, communicate, and form judgments (Petricini 2024). AI is a medium, and like all media, it is not experienced the same way across all cultures (Trujillo-Liñán and Meneses-Trujillo 2025). To encounter another culture's relationship to AI is therefore to encounter a different sensory and epistemic world that is organized by different histories, institutions, and narratives of technological promise and risk.

This article reports on 'AI Across Borders;' a COIL exchange between students enrolled in undergraduate courses at Penn State Behrend (Erie, Pennsylvania, USA) and Universidad Panamericana (Mexico City, Mexico). The exchange, facilitated through shared readings, Zoom-based dialogues, and collaborative reflection tasks, brought US and Mexican students into sustained cross-cultural encounter around questions of artificial intelligence, with its promises, its risks, and its cultural textures. Using post-exchange survey data alongside pedagogical reflection, we map the post-exchange attitudinal patterns reported by students, identify where their AI ecologies diverged most significantly, and trace the pedagogical implications of those divergences.

Our core argument is twofold. First, AI literacy education, as currently conceived, is insufficiently attentive to the intercultural and ecological dimensions of AI use. Existing frameworks and scales, however sophisticated in their mapping of competencies, have been developed in single-country contexts and have not been tested cross-culturally (Lintner 2024). The result is a kind of epistemological monoculture that promotes literacy frameworks that assume a standard user and a standard AI environment that does not exist. Second, COIL pedagogy, informed by media ecology theory, offers a productive site for interrupting that monoculture and for producing the kind of sustained encounter with AI difference that the current moment demands.

We proceed by reviewing the relevant literature on COIL pedagogy, media ecology and AI, intercultural AI literacy, and the current state of cross-cultural AI literacy measurement. We then describe the pedagogical design of AI Across Borders, present our methods and findings, and interpret those findings through the three-phase framework. We conclude by calling for a broader integration of intercultural AI literacy into global communication education.

2 Literature review

2.1 COIL as intercultural pedagogy

Collaborative Online International Learning (COIL) emerged in the early twenty-first century as a response to the structural limitations of traditional campus-based internationalization. In contrast to study-abroad programs, which are resource-intensive and accessible to relatively few students, COIL pairs courses across national boundaries for sustained collaborative learning using digital communication technologies (Rubin and Guth 2015). The model has been adopted across disciplines and institutions as a scalable approach to internationalizing the curriculum while developing students' intercultural communicative competence. Intercultural communicative competence refers to the knowledge, skills, and dispositions required to communicate effectively and appropriately with people whose cultural frameworks differ from one's own (Byram 1997).

Communication scholarship further explains this competence through processes such as managing uncertainty and anxiety in intercultural interaction, which shape how individuals interpret and respond to cultural difference (Gudykunst 2004). Communication scholarship provides an important theoretical lens for understanding the pedagogical value of COIL. Gudykunst's work on intercultural communication, particularly his Anxiety/Uncertainty Management (AUM) theory, emphasizes that effective intercultural interaction depends not simply on acquiring knowledge about other cultures but on managing the uncertainty and anxiety that arise when individuals encounter unfamiliar communicative norms (Gudykunst 2004). According to this framework, successful intercultural communication occurs when individuals are able to maintain uncertainty and anxiety within optimal thresholds that allow for mindful engagement rather than defensive or stereotypical responses. Intercultural competence therefore emerges through communicative practice where individuals learn to interpret ambiguous cues, negotiate meaning, and adapt communicative strategies in interaction with others whose assumptions, expectations, and symbolic systems differ from their own.

This communication-centered perspective reframes intercultural competence as an ongoing process rather than a body of cultural knowledge that can be mastered in advance. Structured interaction becomes the key mechanism through which competence develops. Deardorff's (2006) widely used process model of intercultural competence similarly emphasizes that attitudes, knowledge, and skills emerge through iterative engagement with cultural difference, highlighting reflection, interaction, and adaptation as central components of intercultural learning. Within this framework, pedagogical environments that create sustained opportunities for intercultural dialogue become especially important.

What COIL contributes to this tradition is the intentional structuring of such encounters through digital communication environments. Rather than relying on physical mobility alone, COIL pairs students across national contexts and organizes their interaction through networked platforms. From a media ecological perspective, the technological environments through which US and Mexican students interacted (Zoom meetings, shared discussion, and AI-assisted writing tools) are not neutral conduits for intercultural exchange. As McLuhan (1964) and Meyrowitz (1985) remind us, communication media function as environments that shape patterns of interaction, visibility, and authority. The platforms through which the COIL exchange unfolded therefore became part of the pedagogical structure itself, influencing how students interpreted one another's perspectives, negotiated cultural differences, and constructed shared understandings. In this sense, the medium of the COIL exchange was not merely the setting for intercultural communication; it was an active component of the curriculum.

Several institutional studies of AI in higher education illuminate the instructional challenges at stake. In one investigation of how teacher messages about AI shape student behavior, the researchers found that students are highly sensitive to institutional framing: specifically, how an instructor positions AI shapes whether students approach it with openness or anxiety (Petricini et al. 2025).

2.2 Media ecology and artificial intelligence

We use the term media ecology to refer to the intellectual tradition that studies how communication technologies shape human perception, social organization, and culture. We use media environment or infosphere to describe the concrete sociotechnical conditions within which students encounter AI in everyday life. This distinction matters because the article draws from media ecology as a scholarly perspective while examining differences between the AI environments inhabited by students across national contexts.

Media ecology, as developed by McLuhan (1964), Postman (1992), and Strate (2006) and others, proceeds from a foundational claim that technologies are not neutral instruments but environments that restructure human perception, cognition, and social organization. McLuhan's insight that "the medium is the message" redirects attention from the content a technology carries to the perceptual and cognitive reorganization it enacts in those who inhabit it. Every communication medium, from the printing press to the telephone to the algorithm, creates a new sensory ratio, privileging certain modes of knowledge while rendering others peripheral or invisible. Meyrowitz (1985) extended this logic to social behavior, demonstrating how electronic media dissolve the boundaries between previously

segregated social situations, collapsing distinctions of age, gender, and status that physical environments had sustained. What unites these thinkers is the ecological premise: human beings do not simply use technologies; they live inside them, and those environments shape who they become.

Artificial intelligence, understood through this ecological lens, is not merely a tool for efficiency or a subject of ethical regulation. It is a medium in the full McLuhan sense: an environment that reorganizes perception and cognition at the structural level, prior to and independent of the intentions of its users or designers. When students interact with a large language model, they are not simply retrieving information; they are inhabiting an epistemic environment that has already organized what counts as relevant, what forms of reasoning are rewarded, and what voices are centered or marginalized. The ecology is invisible, as all environments are, until one exits it long enough to see it, or, as this paper argues, until one encounters someone whose AI ecology is organized differently.

Trujillo-Liñán (2022) offers a philosophically precise account of how McLuhan's theory of media operates through Aristotelian causality, particularly the concept of formal cause. In Aristotle's schema, the formal cause of a thing is its organizing principle – the structure or pattern that makes it what it is, not the material of which it is made nor the agent who made it. McLuhan implicitly applies this logic to media: the formal properties of a medium – its speed, its sensory address, its capacity for interactivity or passivity – determine its effects on human perception and social organization in ways that exceed and precede any particular content. Trujillo-Liñán's analysis illuminates why AI cannot be adequately addressed through content-focused literacy frameworks alone. The form of an AI system – its training data, its reward functions, its language model architecture, its interface design – encodes assumptions about intelligence, relevance, authority, and normalcy that operate structurally, shaping every interaction regardless of what question is asked or what answer is returned. To be AI literate, in this deeper sense, is not simply to know how to use AI tools effectively; it is to recognize the formal logic that organizes the AI environment one inhabits.

This understanding of AI as formal cause has direct implications for cross-cultural AI literacy. If AI systems encode assumptions structurally – in their training data, design choices, interfaces, and institutional uses – then students from different cultural contexts do not merely bring different opinions about AI. They encounter AI through educational, linguistic, and institutional environments that may organize its meaning and use differently. The AI ecology of a student in Mexico City is therefore not simply a geographically displaced version of the AI ecology of a student in Erie, Pennsylvania. Placing these environments in dialogue can make visible the assumptions, expectations, and practices that may otherwise appear natural or universal.

Postman's (1992) concept of technopoly deepens this analysis by naming the cultural formation that media ecology theory warns against most urgently. Technopoly, for Postman, describes a society that has surrendered its moral authority to the sovereignty of technique – a condition in which technology is not merely used but deified, in which efficiency becomes the supreme value and all human activity is reorganized around technological optimization. In a technopoly, questions about purpose, meaning, and the good life are displaced by questions about process, capability, and scale. The human being who once stood as the measure of all things is now measured by the system.

The contemporary AI landscape exhibits precisely these technopolic tendencies. The discourse surrounding AI in higher education – dominated by productivity gains, competitive advantage, and workforce readiness – reflects what Trujillo-Liñán (2020) identifies as the colonization of educational discourse by instrumental reason: the reduction of educational purposes to measurable, optimizable outputs. Byung-Chul Han (2010) diagnoses the contemporary form of this colonization as the achievement society, in which the subject internalizes the demands of optimization so thoroughly that exploitation becomes self-exploitation. In the AI-mediated achievement society, students are not coerced into algorithmic dependency; they adopt it voluntarily, because the AI environment has made it seem not merely useful but natural and inevitable.

What is at stake in this dynamic, as Floridi (2014) argues, is nothing less than the integrity of self-formation – the processes through which persons construct a coherent, reflexive identity in relation to the world and to others. Floridi's information philosophy frames the self as an informational organism, a pattern of data that is continuously constructed and reconstructed through interaction with the informational environment. When that environment is an AI system that preemptively organizes what is knowable, writable, and thinkable, the conditions for genuine self-formation are structurally compromised. Trujillo-Liñán (2024) extends this concern into the specifically Latin American educational context, arguing that AI systems shaped by unevenly represented languages, cultural assumptions, and institutional priorities risk constituting a new form of epistemic colonization – not through overt imposition, but through the quiet reorganization of what appears natural, relevant, and well-formed. For students whose linguistic and cultural frameworks are already marginalized in global knowledge systems, the ecological surrender to technopoly is not an abstract philosophical risk; it is a daily encounter with systems that consistently position their ways of knowing as secondary or non-standard.

Media ecology thus argues not merely for AI literacy as skill acquisition but for AI literacy as ecological consciousness: the capacity to recognize the media environment one inhabits, to see its formal logic, to resist its technopolic tendencies, and

to form oneself in relation to it rather than simply within it. This is what distinguishes a media ecological approach from competency-based AI literacy frameworks. Where the latter ask what students can do with AI, media ecology asks what AI is doing to students – and, crucially for this project, whether it is doing the same thing to students in different cultural contexts (Floridi 2014; Han 2010; Postman 1992; Trujillo-Liñán 2020; Trujillo-Liñán 2024).

Recent scholarship in media ecology has further developed the relationship between formal cause and digital environments, emphasizing how computational systems operate as structuring conditions rather than neutral tools (Nystrom 2021; Strate 2006). In this sense, generative AI systems such as LLMs make visible the operation of formal cause in particularly explicit ways: their outputs are not merely responses, but manifestations of underlying probabilistic structures shaped by training data, linguistic hierarchies, and optimization logics. This reinforces McLuhan's insight that the effects of a medium are located in its form rather than its content.

This perspective also aligns with broader critiques of algorithmic systems as socio-technical infrastructures that encode power relations and epistemic hierarchies (Benjamin 2019; Noble 2018; O'Neil 2016).

2.3 Intercultural AI literacy and equity

Emerging cross-cultural research foregrounds the equity dimensions of AI literacy alongside its competency dimensions. As this article proposes, Intercultural AI Literacy (ICAL) is a provisional conceptual lens describing the capacity to recognize and negotiate the cultural, ethical, and ecological situatedness of AI. The conditions under which this capacity develops are not evenly distributed. Students encounter AI through educational systems, institutional policies, linguistic contexts, and material resources that differ across contexts. These differences should not be reduced to a simple binary between technologically dominant and subordinate cultures. Rather, ICAL calls attention to the uneven environments through which AI becomes meaningful and to the ways those environments shape assumptions about access, authority, ethics, and appropriate use. AI literacy frameworks that omit this structural dimension risk treating AI as culturally neutral and universally experienced.

2.4 Cross-cultural AI literacy: measurement gap

The field of AI literacy has generated a substantial body of measurement work in recent years. Long and Magerko's (2020) foundational framework identified seventeen competencies organized around five questions: What is AI? What can AI do?

How does AI work? How should AI be used? How do people perceive AI? Subsequent instruments, including the Meta AI Literacy Scale (MAILS; Carolus et al. 2023), the SNAIL (Laupichler et al. 2023), and the Digital Promise framework (Mills et al. 2024), have elaborated and refined these competency domains, adding dimensions of self-efficacy, metacognition, and domain-specific application. Ng et al. (2021) and Lintner (2024) have provided useful syntheses of this growing literature.

International bodies have joined this effort. UNESCO (2024) released AI competency frameworks for students and teachers that foreground human rights and cultural diversity as guiding principles. The OECD (2025) is developing a global AI literacy framework, and the Digital Education Council (2025) has explicitly named domain expertise as a fifth pillar alongside technical understanding, critical thinking, ethics, and human-centered design. These developments signal growing recognition that AI literacy is a global concern that requires internationally applicable frameworks and instruments.

Yet despite this proliferation of frameworks and scales, a critical gap remains. As Lintner's (2024) systematic review observed, none of the existing AI literacy scales have been cross-culturally validated. Most were developed in single-country contexts – predominantly the United States, Western Europe, or East Asia – and assume a relatively homogeneous user population. Korte et al. (2024) is a notable exception: their study of cross-cultural AI literacy workshops demonstrated that structured international collaboration produces AI literacy gains that single-country instruction does not achieve, suggesting the value of the very model this paper reports. Korte et al. did not theorize the mechanism of that gain, what precisely it is about cross-cultural encounter that produces deeper AI literacy. This paper proposes that the mechanism is I*ntercultural AI Literacy, or the specific capacity, developed through sustained cross-cultural encounter, to recognize and negotiate the cultural, ethical, and ecological situatedness of AI.*

Our survey instrument, described in the Methods section, was adapted from established AI literacy frameworks (Carolus et al. 2023; Lintner 2024; Long and Magerko 2020) and supplemented with items designed to capture cross-cultural and relational dimensions of AI literacy. Rather than constituting a formally validated scale, the instrument should be understood as an exploratory measurement approach used to examine patterns across two national contexts and to inform future scale development.

Administered in both the US and Mexican contexts after the exchange, it creates a unique cross-national dataset allowing us to map some attitudinal patterns students reported following the collaboration. Prior work by Petricini et al. (2024) on AI perceptions across institutional contexts informed the instrument's design philosophy that student attitudes toward AI are powerfully shaped by communicative environments, not merely by technical familiarity.

3 Pedagogical design

3.1 Institutional contexts

AI Across Borders was designed as a COIL exchange between four undergraduate courses: 'AI and the Human Experience;' at Penn State Behrend, taught by Tiffany A. Petricini, and Media Theory, Cultural History and Intersubjective Communication at Universidad Panamericana, Mexico City, taught by Laura Trujillo-Liñán. The exchange was structured around five collaborative modules distributed across a six-week period within the broader academic semester. The design was informed by COIL principles and the constructivist AI pedagogy outlined in García-López and Trujillo-Liñán (2025).

The course at Penn State Behrend engaged students in critical examination of AI across multiple dimensions: technical, ethical, communicative, and cultural. Students encountered media ecology theory alongside AI literacy scholarship, engaged with case studies of algorithmic bias and AI harm, and completed weekly reflective writing tasks. The curriculum's design was informed by prior work embedding AI literacy in the communication courses and by the conviction that effective AI literacy education requires not just competency development but the formation of a reflective, dialogically oriented stance toward AI and its cultural conditions.

The Mexican cohort participated in the exchange in English, which was a non-native language for many of the students. This linguistic dimension is relevant to Intercultural AI Literacy because students were asked to negotiate meaning across both national and linguistic differences while discussing AI systems that may themselves perform unevenly across languages. Although the present study did not systematically analyze the linguistic dimensions of the student interactions, future iterations should examine how native-language reflection, multilingual AI use, and AI-supported translation shape intercultural understanding.

In this context, the design of the exchange was guided by a media ecological proposition: that the most powerful learning environment is not one that delivers content about AI but one that enacts an encounter with AI difference. McLuhan (1964) observed that the environment is the curriculum, that is, that what a medium does to perception matters more than what it says about itself. The COIL exchange was designed as an environment in which AI would inevitably appear differently: in different languages, through different institutional experiences, carrying different cultural weight. That difference was the curriculum.

3.2 COIL collaboration structure

The collaborative exchange unfolded in several structured phases designed to support both intercultural dialogue and collaborative production. Students were first paired across institutions and asked to establish initial contact with their international partner. During their first synchronous meeting, they conducted guided interviews using a shared set of questions designed to prompt discussion about their educational contexts, personal experiences with artificial intelligence, and perceptions of AI's role in communication, creativity, and academic work. This initial conversation served both as an intercultural introduction and as a way of surfacing differences in how students encountered and interpreted AI within their respective educational environments.

Following this initial exchange, partners remained in contact over the next three weeks as they worked together to develop a short podcast episode addressing AI-related themes that emerged from their conversations. The collaborative assignment required students to co-produce multiple components of the project, including the podcast audio, a written description or "blurb" introducing the episode, and a visual image or logo representing the project. These tasks required students to negotiate ideas, divide responsibilities, and coordinate creative decisions across national and technological boundaries.

At the conclusion of the collaboration, students completed an independent critical reflection examining what they had learned through the exchange. These reflections invited students to consider how their assumptions about artificial intelligence, communication, and academic practice had been challenged or reinforced through interaction with their partners. Following completion of the exchange, students also completed a survey measuring AI attitudes, confidence, and cross-cultural orientation. The survey was designed to assess how participants understood AI and intercultural AI literacy after the collaborative experience.

Structured reflection was a central component of the pedagogical design. Students were encouraged to notice and articulate moments of surprise or dissonance in their partners' perspectives on AI. This reflective dimension became especially important for the analytical framework developed in the Discussion section. Ethical AI literacy requires not only technical competence but also the kind of productive disorientation that intercultural encounter can generate. Encountering alternative AI practices and assumptions can reveal the often-invisible infrastructures shaping one's own technological environment, making visible the cultural and institutional conditions under which AI is understood and used.

The exchange therefore serves two related but distinct roles in this study. First, it provides the pedagogical context in which students engaged questions of AI across

cultural and institutional difference. Second, it motivates the ICAL framework developed in the Discussion. The post-exchange survey does not independently establish that the COIL activities caused measurable growth in ICAL; rather, it maps patterns reported by students following the exchange and identifies questions for future longitudinal assessment.

4 Methods

The central empirical component consisted of a post-exchange survey measuring multiple dimensions of AI literacy attitudes among undergraduate students in the United States and Mexico. Administered at the conclusion of the six-week COIL exchange, the survey was analyzed to identify similarities and differences in how students across the two institutional and national contexts reported their attitudes toward AI, confidence using AI, and cross-cultural AI orientation. Because the study did not include a pre-exchange survey or a comparison group, the findings should be interpreted as post-exchange patterns rather than as direct measures of change attributable to the COIL intervention.

This article presents a primarily quantitative, exploratory assessment. The survey data constitute the empirical dataset analyzed in this article. Student reflections, collaborative podcasts, and instructor observations informed the pedagogical interpretation of the exchange but were not systematically coded or analyzed as qualitative data. Accordingly, these materials are discussed as contextual and pedagogical evidence rather than as qualitative findings.

Ethical approval for the study was obtained from the Penn State Institutional Review Board (Protocol No. [REDACTED FOR REVIEW]). Participation was voluntary and anonymous, and all students provided informed consent prior to completing the survey. Data collection procedures complied with institutional guidelines at both participating institutions.

A total of 150 students completed the survey and constitute the analyzed sample (US: n = 55; MX: n = 95). Both cohorts were predominantly first- or second-year undergraduates. US students were drawn from a required humanities general education course ('AI and the Human Experience') at a public university in the northeastern United States; MX students were enrolled in a technology and society course at a private university in Mexico City.

Because participants were enrolled in distinct courses taught by different instructors in different institutional contexts, student responses may reflect course framing, instructor messaging, and local policy discourse in addition to broader national differences. We therefore interpret the findings as emerging from educational environments rather than nationality alone.

Although all collaborative deliverables and synchronous exchanges were conducted in English, Mexican students were not restricted from reasoning in Spanish or from using AI-supported translation tools (e.g., DeepL, Google Translate, or LLM-based translation) when preparing their contributions. Because this language processing was neither required nor systematically documented, its extent is not characterized here.

The survey instrument comprised 20 Likert-scale items (1 = Strongly Disagree, 5 = Strongly Agree) organized into three theory-informed item groupings used as exploratory composite indices, plus three open-ended items and a demographic battery. All items were administered in English. IRB approval was obtained at the US institution; data collection was conducted at the conclusion of the six-week COIL exchange. Our use of AI self-efficacy draws on Bandura's concept of self-efficacy as an individual's belief in their capacity to organize and execute actions required to achieve desired outcomes. In this context, AI self-efficacy refers not simply to technical skill, but confidence in one's ability to use AI tools effectively, critically, and responsibly in academic and communicative settings.

4.1 Theoretical grounding of the instrument

The instrument was not designed as a unidimensional measure of AI competence. It was structured to operationalize the media-ecological premise guiding this study: that AI functions as an environment whose formal organization shapes perception prior to, and independently of, any particular use (McLuhan 1964; Trujillo-Liñán 2022). Following McLuhan's adaptation of the Gestalt distinction between *figure* and *ground* (McLuhan and McLuhan 1988), what users consciously attend to – the figure: the tool, the task, the visible content – is perceptually separable from the environment that organizes that attention – the ground: the institutional, linguistic, and infrastructural conditions through which AI is encountered. Because environments are, on McLuhan's account, invisible to those who inhabit them, a measurement strategy adequate to media ecology cannot rely on a single self-report construct. It must distinguish what students can consciously report about their own capability from the differently organized environments that condition that capability, and it must include a measure of the perceptual shift through which an environment becomes visible. The three composite groupings correspond to these three theoretical layers.

The first grouping, AI self-efficacy (AISE), operationalizes the *figure*: the student's conscious, foregrounded relationship to AI as a usable instrument. Here we draw on Bandura's (1997) concept of self-efficacy applied to the critical, ethical, and communicative use of AI. We retain Bandura deliberately and do not derive

self-efficacy from McLuhan, because the two operate at different levels: Bandura supplies the agentive, individual construct, while media ecology specifies its theoretical position. AISE measures the visible figure – the layer of capability students can introspect and articulate. Media ecology predicts that this figure-level confidence may remain stable across environments that are in fact organized very differently, precisely because confidence in use does not require awareness of the ground.

The second grouping, cross-cultural AI orientation (CCAI), operationalizes the perceptual mechanism by which the ground becomes visible. McLuhan argued that an environment is perceptible only against an *anti-environment* – that we apprehend the ground we inhabit only when a contrasting environment throws it into relief (McLuhan 1964; McLuhan and McLuhan 1988). The cross-cultural encounter at the center of COIL functions as precisely such an anti-environment: the partner's differently organized AI ecology is the contrast that renders one's own ecology available to perception. CCAI items ask students to report this capacity – to recognize and question their assumptions about AI, to apply AI across cultural and national boundaries, and to attend to the ethical and cultural situatedness of AI systems. This is where media ecology and intercultural communicative competence converge. The intercultural competence tradition (Byram 1997; Deardorff 2006; Gudykunst 2004) theorizes the disposition to interpret, negotiate, and adapt across cultural difference; media ecology specifies *what* is being made perceptible through that negotiation – namely the formal organization of differently inhabited AI environments. CCAI is therefore the construct most directly named by Intercultural AI Literacy and the one in which the two traditions are jointly operationalized.

The third grouping, attitudes toward AI in higher education (AIED), operationalizes the *ground* itself: the institutional and infrastructural environment – the local infosphere (Floridi 2014) – through which students encounter AI. Its items index prior exposure, default-use norms, perceptions of threat, institutional clarity, and AI-related anxiety: not a disposition of the student but a description of the environment the student inhabits. This positioning predicts, and helps explain, the grouping's low internal consistency. An environment is not a latent psychological trait, and media ecology gives no reason to expect the conditions that constitute an AI ecology – exposure, governance, affect – to cohere as a single dimension. The exploratory factor structure we report is consistent with this expectation: the AIED items behave as a field of environmental conditions rather than as a unidimensional construct, which is why we report them at the item level and interpret the strongest divergences as ecological signals (Table 1).

For exploratory analysis, the items were organized into three multi-item groupings. Items were selected and adapted to capture theoretically distinct but related constructs: AI skill confidence, cross-cultural AI orientation, and attitudes toward AI in the higher education context.

Table 1: Sample demographic summary.

Characteristic	US (*n* = 55)	MX (*n* = 95)	Note
Semester standing	Frosh/Soph: 43 (78 %)	Frosh/Soph: 80 (84 %)	Coded 1 = Frosh–4 = Sr
Gender: men	39 (71 %)	44 (46 %)	Coded 1 = man, 2 = woman
Gender: women	13 (24 %)	40 (42 %)	
First-generation	5 (9 %)	9 (9 %)	Coded 1 = yes, 2 = no
Financial aid proxy	Pell: 9 (16 %)	JEF: 13 (14 %)	Pell = US; JEF = MX
Mean age proxy	Primarily Yr 1–2	Primarily Yr 1–2	No direct age item

JEF = Jóvenes Escribiendo el Futuro (Mexican federal scholarship for low-income students). Both are first-generation/socioeconomic indicators comparable across institutions.

Reliability highlights: CCAI achieved excellent internal consistency (α = .880), making it the most internally consistent grouping in the instrument. AISE is acceptable (α = .765). Both scales demonstrated comparable internal consistency within each national subsample (AISE: α = .711 at Penn State, α = .794 at UP Mexico; CCAI: α = .800 at Penn State, α = .901 at UP Mexico), indicating acceptable internal consistency in both contexts.

AIED demonstrated weak internal consistency (α = .504), which did not improve when items were removed individually. Exploratory factor analysis with parallel analysis (5,000 iterations) indicated a three-factor structure rather than a single dimension, organized around AI-as-threat (AIED3, AIED5), institutional clarity (AIED6, AIED7), and AI anxiety (AIED8, AIED9). Three items (AIED1, AIED2, AIED4) did not load on any factor, functioning as standalone descriptive items; two of these: prior AI exposure (AIED1/Q18) and default-use behavior (AIED4/Q21), are the items reported individually in the Findings. Within-country reliability analysis confirmed this is a structural issue rather than a cross-cultural measurement artifact: AIED alpha was .296 at Penn State and .241 at UP Mexico – nearly identical and equally weak in both subsamples. Spearman-Brown coefficients for the three two-item pairs ranged from .456 to .589, below the conventional .70 threshold. AIED is therefore not treated as a unidimensional composite; item-level analyses are reported instead.

5 Findings

The post-exchange patterns reported by US and Mexican students were simultaneously convergent and divergent. The cohorts reported substantial similarities in AI confidence and cross-cultural orientation, alongside differences at the level of individual items and demographic subgroups. We interpret these findings as exploratory patterns associated with the pedagogical context of the collaboration rather than as direct measures of change over time.

Composite – level comparisons

On the AISE composite, no significant difference was found between US (M = 4.07, SD = 0.67) and Mexican (M = 4.10, SD = 0.76) students (U = 2,362, p = 0.548, r = 0.059).

Both groups reported similarly high levels of AI self-efficacy, which is a finding that challenges assumptions of unidirectional technological advantage along national lines. On the CCAI composite, the two groups were virtually indistinguishable (US $M = 4.12$, SD = 0.55; MX $M = 4.07$, SD = 0.82; $U = 2{,}267$, $p = 0.501$, $r = 0.067$), suggesting that a strong cross-cultural orientation toward AI is shared across both populations. This convergence is itself pedagogically significant: students in both cohorts reported a strong cross-cultural orientation following the exchange, providing a productive affective foundation for the COIL design.

The AIED item grouping produced an exploratory between-group pattern (US $M = 3.26$, SD = 0.43; MX $M = 3.41$, SD = 0.57; $U = 1818$, $p = 0.045$, $r = 0.202$). However, because the grouping demonstrated weak internal consistency ($\alpha = 0.504$), it should not be interpreted as evidence of a stable underlying construct or as a definitive difference in general attitudes toward AI in higher education. The item-level findings reported below are more analytically informative because they identify the specific dimensions on which the cohorts differed.

Item-level divergences: ecological signals

The most theoretically productive findings emerged at the level of individual items (see Table 2). Two items showed large and highly significant differences between groups, functioning as what we term contextual indicators–evidence of meaningfully different AI environments shaping student perceptions and reported practices (Tables 3 and 4).

Q18 asked students to rate agreement with the statement, "I learned more about AI in high school than I have in college." Mexican students endorsed this item at dramatically higher rates than US students (MX M = 2.72, US M = 1.70; d = 0.748, $p < 0.001$). This large effect, approaching the threshold conventionally associated with substantial group differences, suggests that Mexican students came to university with more developed prior experiences of AI integration in secondary education. This is not a deficit on the US side but a difference. It is a signal of two distinct educational media ecologies, organized by different secondary school cultures, curricula, and institutional relationships to emerging technology.

Q21, which asked about default AI use behavior, "I use AI tools for my coursework unless I am specifically instructed not to" similarly distinguished the groups (MX M = 3.41, US M = 2.87; $d = 0.449$, $p = 0.009$). Mexican students were more inclined toward AI as a default resource; US students were more conditionally oriented, treating AI use as something requiring explicit permission. This divergence maps onto different institutional cultures of AI governance, different teacher message norms, and the different discursive climates surrounding AI use in higher education that Petricini et al. (2025) have documented.

Table 2: Exploratory item groupings and composite indices.

Composite measure/item	Abbr.	Item text (abbreviated)	α
AI competency (AISE)		5 items	0.765
Q4	AISE1	I can apply AI tools to support my learning or work	
Q14	AISE2	I can evaluate the accuracy of AI-generated content	
Q13	AISE3	I can use AI to create original work while maintaining my own voice	
Q12	AISE4	I can identify and apply ethical guidelines for AI use	
Q11	AISE5	I can use AI in ways that strengthen my communication	
Cross-culturaL AI literacy (CCAI)		6 items	0.880
Q10	CCAI1	I have been exposed to cross-cultural AI perspectives	
Q9	CCAI2	I can apply AI ideas across cultural/national boundaries	
Q8	CCAI3	I reflect on and question my assumptions about AI	
Q7	CCAI4	I can apply AI tools taking into account cultural insights	
Q6	CCAI5	I can create AI work sensitive to diverse cultural perspectives	
Q5	CCAI6	I can discuss AI ethics that emerge differently across cultures	
AI in higher education (AIED)		9 items	0.504
Q18	AIED1	I learned more about AI in high school than in college	
Q19	AIED2	AI tools will be necessary for success in my career field	
Q20	AIED3	I think AI is ruining my college education	
Q21	AIED4	Unless told not to, I will use AI on assignments/exams	
Q22	AIED5	I believe using AI harms my intellectual development	
Q23	AIED6	I understand when I can/cannot use AI in college	
Q24	AIED7	I have received the guidance I need on AI policy	
Q26	AIED8	AI causes me stress/anxiety about decision-making	
Q27	AIED9	I am worried about being accused of using AI when I haven't	

5.1 Equity-relevant subgroup effects

A particularly consequential set of findings emerged from subgroup analyses examining financial aid eligibility and gender (Table 5).

Among US students, those eligible for the Federal Pell Grant showed significantly lower AISE scores than non-Pell students (Pell M = 3.73, No-Pell M = 4.28; d = 0.905, p = 0.042). A Cohen's d of 0.905 represents a large effect, one of the largest in our dataset, indicating that within the US context, economic precarity is associated with substantially lower AI self-efficacy. This finding resonates with the information inequity framework applied to generative AI by Zipf et al. (2025), which documents

Table 3: Composite-level comparisons: US and mexican Students.

Composite measure (items, α)	US M (SD)	MX M (SD)	*U*	*p*	*r*	Interpretation
AISE – AI self-efficacy (5, α = 0.765)	4.07 (0.67)	4.10 (0.76)	2,362	0.548	0.059	Non-significant; shared confidence
CCAI – Cross-cultural AI (6, α = 0.880)	4.12 (0.55)	4.07 (0.82)	2,267	0.501	0.067	Virtually identical orientations
AIED – AI in education (9, α = 0.504)	3.26 (0.43)	3.41 (0.57)	1818	0.045*	0.202	Exploratory pattern only; interpret cautiously due to low reliability

All exploratory composite comparisons used Mann-Whitney *U* tests due to non-normal distributions (Shapiro-Wilk $p < 0.05$ in both groups). Effect size *r* = rank-biserial correlation. *$p < 0.05$. US $n = 54–55$; MX $n = 86–93$.

Table 4: Key item-level divergences: ecological signals.

Item	US mean (SD)	MX mean (SD)	Cohen's d	*p*	Interpretation
Q18: Learned more about AI in high school than in college	1.70 (1.18)	2.72 (1.47)	0.748	<0.001***	MX students: More prior AI exposure
Q21: I use AI tools unless specifically told not to	2.87 (1.21)	3.41 (1.21)	0.449	0.009**	MX students: AI as default resource

Both items used Welch's *t*-test. **$p < 0.01$, ***$p < 0.001$.

how differential access to technology, tutoring, and institutional resources produces unequal AI literacy outcomes independent of student ability or motivation.

Among Mexican students, those receiving JEF support showed lower CCAI scores than non-JEF peers (JEF $M = 3.61$, No-JEF $M = 4.27$; $d = 0.804$, $p = 0.062$), a large effect that approached but did not reach conventional significance, likely due to the small JEF subsample ($n = 13$). This finding is treated as a meaningful trend warranting

Table 5: Equity-relevant subgroup effects.

Subgroup	Context	Composite measure	Cohen's d	*p*	Interpretation
Pell-eligible vs. non-Pell	US	AISE	0.905	0.042*	Large; economic precarity → lower AI confidence
JEF-eligible vs. non-JEF	MX	CCAI	0.804	0.062	Medium-large; precarity → lower cross-cultural AI orientation
Women vs. men	US	CCAI	0.747	0.041*	Medium-large; women higher on cross-cultural orientation

All comparisons used Welch's *t*-test. *$p < 0.05$.

replication with larger samples. Taken together, these findings suggest that economic resources may shape students' encounters with AI across national contexts, although the patterns should be interpreted cautiously. The US and Mexican subgroup analyses involve different measures, and the Mexican comparison did not reach conventional statistical significance. These exploratory signals warrant replication with larger samples and call attention to the importance of material conditions of AI access alongside cultural difference.

Within the US sample, women demonstrated significantly higher CCAI scores than men (Women $M = 4.41$, Men $M = 4.03$; $d = 0.747$, $p = 0.041$), suggesting that female-identifying students were more strongly oriented toward the cross-cultural dimensions of AI literacy. This exploratory finding warrants further study with a larger and more balanced sample. The present analysis does not establish the mechanisms underlying the observed difference.

6 Discussion

Read through the figure/ground architecture that organized the instrument, the convergence-with-divergence pattern is not an anomaly but a confirmation of the media-ecological premise. The two cohorts report nearly identical self-efficacy (the figure) while differing on prior exposure and default use (the ground). This is what media ecology predicts: confidence in using a medium is a figure-level phenomenon that does not, on its own, reveal the differently organized environment in which that confidence was formed. The empirical task of an intercultural AI literacy instrument is therefore not to detect differences in competence but to detect differences in *environment* beneath comparable competence – and to register, through CCAI, the perceptual capacity by which those environmental differences can be brought into view.

Immersion – entering the ecology

The first phase of Intercultural AI Literacy is Immersion: the condition of being embedded in a particular AI media ecology without yet being fully aware of its contours. McLuhan (1964) observed that environments are invisible to their inhabitants precisely because they are environments – the total perceptual surround within which experience is organized. Fish, as the proverbial saying goes, do not notice water. Students who have grown up with particular AI tools, trained by particular institutional and cultural contexts to understand AI in particular ways, are immersed in their AI ecology in this sense: it shapes their questions, their defaults, their anxieties, and their assumptions about what AI is and does, without presenting itself as a contingent cultural formation that might be otherwise organized.

The Immersion phase is not a deficiency to be corrected but an unavoidable starting condition to be made pedagogically productive. Before US and Mexican students could encounter one another's AI ecologies, they needed to become aware that they were inside their own. The opening weeks of the AI Across Borders exchange were designed with this aim: to prompt students to notice the AI environment they already inhabited before asking them to compare it to another. Readings drawn from media ecology theory, alongside reflection prompts asking students to reconstruct their own histories of AI encounter – when they first used it, what they were told about it, what institutions shaped their access to it – served to surface the ecological conditions that had previously been invisible (Floridi 2014; McLuhan 1964).

Floridi's (2014) framework of the infosphere – the total informational environment in which persons are embedded as informational organisms – provides a conceptual vocabulary for understanding what is at stake in the Immersion phase. For Floridi, the infosphere is not an external resource that persons access; it is the constitutive medium of personal identity and social life. To become aware of one's AI ecology is therefore not merely to acquire technical knowledge about a set of tools; it is to develop a reflexive relationship to the informational environment through which one's own knowing and being-in-the-world is organized. Trujillo-Liñán (2024) situates this reflexive self-awareness within the specifically Latin American educational context, arguing that students whose AI encounters have been mediated by institutions with different relationships to global AI infrastructure arrive at the Immersion phase with different prior formations – and that making those differences explicit is the first step toward genuine intercultural AI dialogue. It is precisely the contrast produced by the COIL encounter that renders the ecology visible: the ecology is invisible until contrasted (Floridi 2014; McLuhan 1964; Trujillo-Liñán 2024).

Encounter – recognition across difference.

The encounter phase is where the distinctive pedagogical work of COIL becomes most visible. In the collaborative sessions, students were not merely exchanging opinions about AI. They were practicing the full complexity of cross-cultural communication and establishing credibility across contexts where authority is configured differently, recognizing the emotional weight that AI carries in another culture's life, and making arguments whose force depended on genuine attention to the other's framework of understanding.

This complexity is best understood not through a formulaic taxonomy of communicative moves but through the rhetorical tradition's understanding of persuasion as a relational achievement. Communication scholars from Aristotle onward have recognized that effective communication requires deep adaptation to one's interlocutor by attending to who the other is, what they value, and how they make sense of the world. In a cross-cultural AI exchange, this adaptation is nontrivial. The question of who counts as a credible authority on AI, whether an

experienced practitioner, a critical humanist, a technically trained engineer, a student who learned about AI in secondary school, is answered differently in different cultural contexts. Recognizing and negotiating this difference is itself a form of literacy.

Trujillo-Liñán's (2022) analysis of formal cause in McLuhan's thinking is particularly illuminating here. Her argument that McLuhan's media theory operates according to an Aristotelian logic, or that the formal properties of a medium determine its effects in ways that precede and exceed its content, helps explain why the encounter phase of COIL is not simply about what students say to one another, but about the conditions under which they say it. The form of the exchange such as the affordances of Zoom, the asynchrony of written reflection, the shared but differently inhabited digital spaces, shapes what kinds of recognition are possible. Students were not merely communicating across a cultural gap; they were doing so within and through media environments that have their own formal logics.

Reflection – toward critical AI literacy

The Reflection phase describes the pedagogical aim of moving from AI as an environmental backdrop toward AI as an object of critical examination. In this phase, students are invited to consider AI as a technology with a history, a cultural location, and a political economy. Because the reflections were not systematically coded as qualitative data, the present study does not claim to document this movement empirically. Rather, reflection is proposed as a necessary component of the ICAL framework.

The movement that this framework seeks to cultivate is what Postman (1992) had in mind when he called for a loving resistance fighter stance toward technology: not technophobia or rejection, but the capacity to step outside the technological environment long enough to see it for what it is. COIL creates the conditions for this stepping outside by making the invisible visible: when a Mexican student describes AI as something integrated into their secondary schooling, a US student's implicit assumption that AI is a distinctly college-level encounter is no longer invisible. It becomes an artifact of a specific educational context – something to be thought about rather than simply lived within.

Trujillo-Liñán and Meneses-Trujillo (2025) argue that digital literacy as the capacity to understand how digital media shape perception and decision-making is a prerequisite for genuine freedom in the connected society. Their analysis of McLuhan's insight that the medium shapes the user, not merely the message, provides the media ecological grounding for what the Reflection phase of ICAL aims to produce: not simply students who can use AI effectively, but students who understand how their relationship to AI has been formed and who can therefore form it more intentionally. This is the difference between AI competency and AI literacy in the

deepest sense of the term, that is, the capacity for reflective, critical engagement with a medium that has become one's environment.

The Q21 divergence is particularly evocative in this context. That Mexican students were more likely to use AI tools by default, while US students waited for explicit permission, is not simply a behavioral difference. It encodes different relationships to institutional authority, different cultures of academic integrity, and different histories of AI in educational discourse (Petricini et al. 2025). Helping students on both sides recognize that their default orientation to AI is not natural but culturally and institutionally shaped is a central aim of the Reflection phase.

Because these measures are exploratory composites rather than validated latent constructs, the discussion emphasizes interpretive patterns and pedagogical implications rather than definitive measurement claims.

6.1 Equity and decolonial dimension

The subgroup findings point toward a structural dimension of intercultural AI literacy that competency frameworks have often neglected: the material conditions under which students encounter AI. Among US students, Pell-eligible students reported lower AI self-efficacy than non-Pell students. Among Mexican students, JEF recipients reported lower cross-cultural AI orientation than non-JEF peers, although this difference did not reach conventional statistical significance. Because these findings involve different measures and relatively small subsamples, they should be treated as exploratory signals rather than as evidence of a single cross-national mechanism. They suggest the need for further research examining how economic resources, institutional support, and access to technology may shape students' AI experiences.

Noble (2018) and Benjamin (2019) have demonstrated that algorithmic systems are not neutral technologies accidentally shaped by particular interests but artifacts of specific historical, economic, and social formations. They emerge within unequal institutional contexts and can reproduce the assumptions, priorities, and exclusions embedded within those contexts. O'Neil's (2016) analysis of algorithmic discrimination further demonstrates how computational systems can perpetuate structural inequalities without transparency or meaningful recourse. For COIL pedagogy, the relevant point is not that AI belongs to a single national culture, but that students encounter AI within differently resourced and differently organized educational environments.

This unevenness should not be understood as a simple geographic binary. AI systems emerge through transnational networks of development, data, and use. The

relevant pedagogical question is how unequal access, institutional support, and cultural framing shape students' encounters with AI across contexts.

For COIL pedagogy, this means that genuine intercultural AI literacy cannot stop at the recognition of cultural difference. It must include the recognition of structural inequality and the ways in which different AI ecologies are not merely different but differently resourced, differently valued, and differently positioned in global hierarchies of knowledge and power. Zuboff's (2019) account of surveillance capitalism, extended by Trujillo-Liñán and Meneses-Trujillo (2025) to the realm of digital rights, illuminates the political economy of this inequality, drawing attention to the ways data extraction and uneven protections can reinforce existing inequalities.

The practical implication is clear: COIL exchanges that bring together students across economic as well as national difference need to attend to material conditions of AI access, to offer scaffolding for students with fewer prior resources, and to make the structural dimensions of AI inequality part of the explicit curriculum. Intercultural AI literacy that omits the decolonial dimension risks reproducing the asymmetries it purports to address.

7 Limitations

Several limitations of this study warrant acknowledgment. The survey instrument, while adapted from established AI literacy frameworks and supplemented with cross-cultural items, has not yet undergone formal cross-cultural psychometric validation; Lintner's (2024) systematic review demonstrates that the absence of cross-cultural validation is a field-wide gap, and our instrument shares this limitation. In addition, the grouped items used in this study function as exploratory composites rather than psychometrically validated scales. The multidimensionality of the AIED battery was investigated through exploratory factor analysis with parallel analysis, which suggested a three-factor structure; however, this solution is exploratory and derived from a single sample (n = 137), and the resulting two-item groupings yielded Spearman-Brown coefficients below conventional reliability thresholds (0.456–0.589). Future research should employ confirmatory factor analysis on an independent sample, cross-cultural invariance testing, and larger multisite datasets to refine and validate measurement of Intercultural AI Literacy. The sample, while providing a unique two-country dataset, is drawn from a single COIL exchange at two institutions and may not be representative of broader student populations in either the United States or Mexico. Because the survey was administered only after the exchange and did not include a pre-test comparison, the study cannot determine the magnitude of attitudinal change attributable to the COIL intervention. Findings should therefore be interpreted as post-exchange patterns

rather than direct measures of growth over time. In addition, because participants were enrolled in different courses taught by different instructors, student responses may also reflect course design, instructor framing, and institutional policy discourse. Future research should pursue longitudinal designs that follow students through the full arc of the Immersion, Encounter, and Reflection phases; cross-cultural validation of AI literacy instruments with large and diverse samples from multiple national contexts; structural equity analyses that attend explicitly to the material conditions of AI access rather than treating them as demographic covariates; and comparison of whether earlier normalized exposure to AI or more guarded, critically scaffolded introduction produces stronger long-term educational outcomes. UNESCO's (2024) framework and Zipf, Wu, and Petricini's (2025) information equity analysis provide productive theoretical resources for this agenda. The ICAL framework is offered not as a completed edifice but as a provisional architecture-an invitation to the global communication education community to build, test, and critique.

8 Conclusions

This article has argued that prevailing approaches to AI literacy insufficiently address the intercultural and ecological dimensions of artificial intelligence. Drawing on media ecology theory and an exploratory post-exchange survey of undergraduate students at Penn State Behrend and Universidad Panamericana, we have proposed Intercultural AI Literacy (ICAL) as a provisional conceptual framework for recognizing, analyzing, and negotiating the cultural, ethical, and ecological dimensions of AI across contexts of difference. The findings identify post-exchange differences in reported prior educational exposure to AI, default AI-use behavior, and equity-relevant subgroup patterns. Because the study did not include a pre-test or comparison group, these findings should not be interpreted as causal effects of the COIL intervention. Instead, they demonstrate the importance of examining AI literacy within the institutional, cultural, and material environments through which students encounter emerging technologies.

The central proposition of this paper is that structured encounters with AI difference can deepen literacy in ways that may be difficult to achieve through single-context instruction alone. When students encounter peers whose assumptions about AI have been shaped by different educational experiences, institutional expectations, and discursive climates, their own environments can become visible as environments rather than simply as "the way things are." The encounter is designed not merely to add information but to create conditions for a qualitative shift. This is precisely the movement that Postman (1992) associated with the loving resistance fighter stance toward technology: not the rejection of technology but the capacity to step outside it long enough to see it for what it is.

The implication is that AI literacy must move from competency to ecological consciousness. Competency-based frameworks – however sophisticated in their mapping of technical skills, ethical awareness, and domain-specific application – remain focused on what students can do with AI. They do not, as a rule, ask what AI is doing to students, whose assumptions it encodes, or whether it is restructuring epistemic habits and self-formation processes in culturally differential ways. A media ecological approach insists that these questions are not supplementary to AI literacy but foundational. The form of the AI environment shapes perception and cognition prior to any particular use; literacy in the ecological sense requires the capacity to see that form and to form oneself in relation to it reflexively, critically, and with awareness of the structural inequalities that organize differential AI access and exposure (Floridi 2014; Trujillo-Liñán and Meneses-Trujillo 2025).

COIL is a powerful site for this development precisely because it creates the conditions under which ecological difference becomes visible. The post-exchange survey suggests that undergraduate students across two distinct institutional and national contexts reported strong cross-cultural orientation following the collaboration. This openness, however, is only the beginning. The conceptual framework proposes that literacy may be deepened not through exposure alone, but through structured encounter, critical reflection, and sustained engagement with difference.

Ultimately, the goal of intercultural AI literacy is not merely understanding but agency. Students are not passive recipients of AI environments; they are participants in their ongoing formation. The pedagogical challenge, therefore, is to cultivate the capacity to engage AI not only critically but ethically and intentionally. This means recognizing that their interactions with AI systems contribute to shaping the norms, expectations, and practices that define these environments.

Intercultural encounters such as those enabled by COIL pedagogy create the conditions for this agency to emerge. By making visible the variability of AI across contexts, students come to see that their own relationship with AI is not fixed but constructed – and therefore open to transformation. AI literacy, in this deeper sense, becomes a practice of self-formation: the ability to position oneself in relation to technological systems with awareness, responsibility, and ethical commitment.

To be AI literate, then, is not only to know how to use AI, but to decide – individually and collectively – how one ought to live with it.

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Informed consent: Informed consent was obtained from all individuals included in this study, or their legal guardians or wards.
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