# Faculty & Instructors Brief

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## *Executive Summary*

Our analysis of 909 education-focused sources this week reveals institutions caught between incompatible frameworks: prohibition and preparation. Research increasingly argues for entirely reframing academic integrity approaches [6], yet faculty continue receiving contradictory enforcement signals from administration, disciplinary associations, and accreditors.

[6] From Prohibition to Preparation: Reframing Academic Integrity in the Age of AI

The central tension: whether AI literacy—understanding what these tools do—suffices, or whether institutions must develop comprehensive AI readiness [2]. French researchers frame this starkly as preserving "le goût de l'effort intellectuel"—the taste for intellectual struggle [23]. This isn't pedagogical nostalgia. It's a claim about what education fundamentally requires—and it conflicts directly with workplace-readiness arguments for AI fluency.

[2] AI Literacy vs Readiness in Universities

[23] «Préserver le goût de l'effort intellectuel» : l'université face ...

Research also documents what happens when AI substitutes for human educational interaction: increased student loneliness and decreased retention [21]. The question facing you isn't whether to integrate AI. It's how to integrate it without undermining the human elements that make education effective.

[21] When artificial intelligence substitutes humans in higher education: the cost of loneliness, student success, and retention

This briefing provides: assessment redesign approaches drawn from cross-continental implementation studies [5], frameworks for developing critical thinking alongside responsible AI use [19], and documented pathways from literacy to institutional readiness applicable to your disciplinary context.

[5] From Intimidation to Innovation: Cross-Continental Multiple Case Studies on How to Harness AI to Elevate Engagement, Comprehension, and Retention

[19] The SAGE framework for developing critical thinking and responsible generative AI use in cybersecurity education

## *Critical Tension*

### *The Specific Tension*

Our contradiction mapping this week did not produce formally structured tension pairs, but the articles themselves reveal a sharp underlying conflict that faculty cannot escape: the simultaneous demand to preserve rigorous intellectual development while preparing students for professional environments where AI fluency is already assumed. The French press crystallizes one pole: «Préserver le goût de l'effort intellectuel» : l'université face ... [23]—the taste for intellectual effort

[23] «Préserver le goût de l'effort intellectuel» : l'université face ...

itself becomes the endangered species. The opposing pole emerges from institutional reports emphasizing readiness: the distinction between understanding AI and being prepared to deploy it professionally [2]. Faculty stand precisely at this fault line, asked to satisfy both imperatives without guidance on their reconciliation.

[2] AI Literacy vs Readiness in Universities

### *Why It's Immediate*

Assignment deadlines don't pause for policy development. Office hours this week will include questions you have no institutional guidance to answer. The temporal mismatch is structural: AI capabilities evolve in months, course approvals take semesters, and curricular reform requires years. Meanwhile, research on trust in generative AI suggests students are already making their own decisions about when and how to use these tools [4]. Your syllabus language—whatever it currently says—will be interpreted, tested, and potentially violated before your institution's task force delivers recommendations. The decisions you make this semester become de facto policy in the absence of de jure guidance.

[4] Exploring trust in generative AI for higher education ... - Nature

### *Why Obvious Solutions Fail*

The prohibition-to-preparation shift documented in recent scholarship [6] acknowledges what many faculty have already discovered: blanket AI bans prove unenforceable and pedagogically counterproductive. Detection tools generate false positives that damage trust and disproportionately flag non-native speakers. Yet the alternative—open integration—collides with legitimate concerns about cognitive development. Researchers have coined the term "cognitive sedentarism" to describe what happens when inquiry becomes query, when the struggle of formulating one's own answer is replaced by the ease of accepting a generated response [1].

[6] From Prohibition to Preparation: Reframing Academic Integrity in the Age of AI

[1] Chat GPT y sedentarismo cognitivo: aprender de consultas a la IA ...

Neither pole offers safety. The loneliness research documents another failure mode: when AI substitutes for human interaction in educational contexts, student success and retention suffer measurably [21]. Even well-intentioned AI integration can inadvertently hollow out the relational dimensions of learning that drive persistence.

[21] When artificial intelligence substitutes humans in higher education:the cost of loneliness, student success, and retention

### *The Hidden Complexity*

The discourse available to guide your decisions is systematically incomplete. Major institutional reports from Toronto [17] and Boston University [15] offer frameworks, but these emerge from well-resourced research universities with dedicated task forces—conditions far from

[17] PDF Toward an AI-Ready University - University of Toronto

[15] PDF Boston University Ai Task Force

universal. Parent perspectives remain almost entirely absent from the conversation, despite their role in student expectations and complaints. Policymaker voices focus on regulation, not pedagogy. Most critically, the students making daily decisions about AI use appear primarily as objects of study rather than participants in the design of policies that govern their education.

What faculty need is not more prescriptive rules from above, but frameworks for making defensible decisions under genuine uncertainty. The SAGE framework for critical thinking and responsible AI use in cybersecurity education [19] offers one model, but its discipline-specific design highlights a further gap: generalizable pedagogical approaches remain scarce. You are being asked to exercise professional judgment in terrain where the profession itself has not yet established consensus.

[19] The SAGE framework for developing critical thinking and responsible generative AI use in cybersecurity education

### *Actionable Recommendations*

The following recommendations emerge from this week's evidence synthesis. A critical caveat: our analysis documents conceptual frameworks and emerging approaches, but longitudinal outcome data remains sparse. What follows represents the best available guidance, not proven formulas.

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**Recommendation 1: Shift from AI Literacy to AI Readiness in Course Design**

FAILURE THIS ADDRESSES

Current approaches often focus narrowly on teaching students what AI tools can do—a literacy model that becomes obsolete as capabilities evolve monthly. The distinction matters: literacy teaches tool mechanics; readiness develops adaptive capacity. [2] documents how institutions conflate these concepts, resulting in training that dates quickly and fails to prepare students for professional contexts where AI integration is expected.

[2] AI Literacy vs Readiness in Universities

THE EVIDENCE-BASED ALTERNATIVE

Rather than dedicating class time to specific tool tutorials, embed AI decision-making into existing disciplinary work. [2] argues that readiness requires developing judgment about when AI assistance is appropriate, how to evaluate its outputs, and how to maintain intellectual ownership while using augmentation tools. [19] offers a structured approach: Situation analysis, AI interaction, Generation evaluation, and Ethical reflection. This moves beyond prohibition or uncritical adoption toward deliberate integration.

[2] AI Literacy vs Readiness in Universities

[19] The SAGE framework for developing critical thinking and responsible generative AI use in cybersecurity education

IMPLEMENTATION TIMELINE

1. Week 1: Audit one assignment for implicit AI assumptions (2 hours) 2. Weeks 2-4: Add explicit AI decision points—where would

assistance be appropriate? Where would it undermine learning objectives? 3. By midterm: Require students to document their AI choices (not just usage) in at least one assignment 4. End of semester: Assess whether students can articulate when NOT to use AI, not just when they did

WHY THIS ADDRESSES THE CORE TENSION

This approach acknowledges that neither prohibition nor wholesale adoption resolves the fundamental tension between efficiency and skill development. By requiring students to make and justify AI decisions, you shift the cognitive work from tool operation to judgment—precisely the capacity that remains valuable regardless of technological change.

REALISTIC OUTCOMES

Direct outcome data is limited. The frameworks cited demonstrate theoretical coherence, but your disciplinary context will determine effectiveness. Expect resistance from students who prefer clear rules to judgment calls.

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**Recommendation 2: Design Assignments That Make AI Use Visible Rather Than Prohibited**

FAILURE THIS ADDRESSES

Detection-focused approaches have documented limitations. [10] details how faculty who rely primarily on detection tools face an arms race they cannot win. [6] argues that prohibition policies fail because they assume a binary (used/didn't use) that no longer reflects actual student work processes.

[10] How college professors are adapting to rampant AI cheating

[6] From Prohibition to Preparation: Reframing Academic Integrity in the Age of AI

THE EVIDENCE-BASED ALTERNATIVE

[17] recommends transparency frameworks where students document AI interactions as part of their intellectual process. [22] explores how writing itself must be reconceptualized when AI is involved—suggesting that the process narrative becomes as important as the final product. Assignments requiring students to submit conversation logs, revision histories, or "intellectual contribution statements" make AI collaboration visible rather than covert.

[17] PDF Toward an AI-Ready University - University of Toronto

[22] Writing with machines? Reconceptualizing student work in the age of AI

IMPLEMENTATION TIMELINE

1. Week 1: Draft a one-paragraph "AI use declaration" requirement for an upcoming assignment (1 hour) 2. Weeks 2-4: Pilot on one assignment; require students to describe what they delegated and what they retained 3. By midterm: Review declarations to identify patterns—are students making thoughtful distinctions or treating it as compliance theater? 4. End of semester: Refine the declaration based on what actually generated useful information

WHY THIS ADDRESSES THE CORE TENSION

This navigates the prohibition-integration tension by changing the

question from ”did you cheat?” to ”what is yours?” Students must claim ownership of specific intellectual contributions, which requires actually making them. The approach accepts that some AI use will occur while preserving accountability.

REALISTIC OUTCOMES

[4] documents significant variance in how students perceive and report AI use. Initial declarations may be superficial. The pedagogical value comes from repeated practice in distinguishing human contribution from machine output—a skill that improves with deliberate attention but requires multiple iterations.

[4] Exploring trust in generative AI for higher education ... - Nature

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**Recommendation 3: Preserve Productive Struggle Through Assignment Structure**

FAILURE THIS ADDRESSES

[23] identifies the core risk: students may lose what the article calls ”le goût de l’effort intellectuel”—the taste for intellectual effort itself. [1] names this ”cognitive sedentarism”—the atrophy that comes from outsourcing mental work. The failure isn’t that students use AI; it’s that courses no longer require the struggle through which expertise develops.

[23] «Préserver le goût de l’effort intellectuel» : l’université face ...

[1] ”Chat GPT y sedentarismo cognitivo: aprender de consultas a la IA ...

THE EVIDENCE-BASED ALTERNATIVE

[9] emphasizes that certain learning objectives require human struggle regardless of AI availability. [16] examines how assignment design can either enable shortcuts or require authentic engagement. Practical strategies include: requiring in-class writing components, designing reflection assignments that can’t be delegated, and sequencing work so early stages must be completed before AI could plausibly assist.

[9] Guía para el uso de IA generativa en educación e investigación

[16] PDF Generative AI in Higher Education Academic Assignments:

IMPLEMENTATION TIMELINE

1. Week 1: Identify one learning objective in your course where struggle is the point (reading difficulty, writing drafts, problem-solving attempts) 2. Weeks 2-4: Design or modify one assignment to protect that struggle—in-class component, oral defense, or process documentation 3. By midterm: Assess whether the protected component reveals student understanding your other assignments miss 4. End of semester: Determine which learning objectives require protection and which benefit from AI augmentation

WHY THIS ADDRESSES THE CORE TENSION

This acknowledges that the efficiency-mastery tension cannot be resolved universally. Some skills require inefficiency; some benefit from AI leverage. The faculty judgment lies in distinguishing which is which—and making that distinction explicit to students.

REALISTIC OUTCOMES

Evidence for specific assignment structures remains limited. [21] documents risks when AI replaces human interaction entirely, but

[21] When artificial intelligence substitutes humans in higher education: the cost of loneliness, student success, and retention

protective assignment design lacks robust outcome studies. Treat this as informed experimentation, not proven practice.

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**Recommendation 4: Develop Discipline-Specific AI Standards Collaboratively**

FAILURE THIS ADDRESSES

Institution-wide AI policies often fail because they cannot address disciplinary specificity. [15] acknowledges this limitation, noting that appropriate AI use varies dramatically between creative writing and data analysis courses. Generic policies create compliance confusion rather than thoughtful practice.

[15] PDF Boston University Ai Task Force

THE EVIDENCE-BASED ALTERNATIVE

[8] and [14] both emphasize the need for context-specific guidance developed with disciplinary expertise. [3] offers a framework adaptable to different contexts while maintaining core principles. The practical action: convene colleagues within your department to develop shared expectations that students encounter consistently across courses.

[8] Generative Artificial Intelligence in Teaching and Learning at McMaster University

[14] Navigating the Complexity of Generative Artificial Intelligence in Higher Education: A Systematic Literature Review

[3] Bridging educational equity gaps: expanding the CHAT-ACTS ... - Springer

IMPLEMENTATION TIMELINE

1. Week 1: Identify 2-3 colleagues teaching related courses; propose a 30-minute conversation about AI expectations 2. Weeks 2-4: Document where your expectations align and diverge 3. By midterm: Draft a one-page departmental guidance document students can reference 4. End of semester: Review with students what reduced confusion and what remained unclear

WHY THIS ADDRESSES THE CORE TENSION

Students navigate the accessibility-authenticity tension more effectively when expectations are consistent and explained. Departmental coherence doesn't resolve the underlying tension but removes the additional confusion of contradictory policies.

REALISTIC OUTCOMES

This recommendation addresses process rather than outcomes. Documented evidence for departmental coordination improving student AI decisions is minimal. The value lies in reducing student confusion and faculty isolation—benefits that may not appear in traditional assessment metrics.

## *Supporting Evidence*

## *Evidence Architecture*

### *Dimensional Patterns*

Our dimensional analysis of this week's corpus reveals asymmetric attention across cognitive categories. Of 1,885 total articles, 909 ad-

dressed education—a 48% concentration suggesting AI in higher education remains a dominant discourse site. However, depth varies considerably.

**Information dimension:** Knowledge production clusters around implementation guidance rather than outcome measurement. Sources like [17] and [15] exemplify institutional positioning documents—heavy on frameworks, lighter on longitudinal evidence. The research base tilts toward adoption patterns over learning outcomes, creating a structural gap between "how to implement" and "whether it works."

[17] Toward an AI-Ready University - University of Toronto

[15] Boston University AI Task Force

**Concepts dimension:** Frameworks converge around a readiness-versus-literacy distinction that [2] makes explicit. The dominant conceptual framing treats AI competence as threshold-based—institutions either cross into "readiness" or remain in "literacy." This binary obscures developmental trajectories and contextual variation. Competing frameworks from [7] suggest regional and disciplinary variation that complicates universal readiness metrics.

[2] AI Literacy vs Readiness in Universities

[7] Generative AI in higher education: A global perspective of ...

**Point of view dimension:** Our corpus exhibits significant perspective asymmetry. Institutional and administrative voices dominate task force reports and policy documents. Student experience appears filtered through survey instruments in sources like [4] and [13], but rarely as direct testimony. Critical perspectives—those questioning whether AI integration should proceed—appear marginally. [23] represents a minority position defending intellectual effort against cognitive offloading.

[4] Exploring trust in generative AI for higher education ... - Nature

[13] Modèles d'acceptation d'une technologie et mécanismes attentionnels: l'adoption de ChatGPT chez les étudiants de l'enseignement supérieur

[23] «Préserver le goût de l'effort intellectuel» : l'université face ...

### *Discourse Patterns*

**Metaphor analysis:** Two competing metaphorical frames structure the corpus. The *transformation* metaphor—appearing in institutional task force documents—treats AI as categorical rupture requiring fundamental reimagination of pedagogy. The *tool* metaphor—more common in practical guidance—positions AI as instrumental augmentation of existing practice. These frames carry distinct implications: transformation rhetoric justifies rapid policy overhaul, while tool rhetoric permits incremental adoption. [19] attempts synthesis, framing AI as tool requiring critical thinking scaffolds—a "tool-with-guardrails" hybrid.

[19] The SAGE framework for developing critical thinking and responsible generative AI use in cybersecurity education

A third frame emerges from critical sources: the *substitution* metaphor. [21] and [1] invoke "cognitive sedentarism"—positioning AI not as transformation or tool but as replacement that atrophies capability. This metaphor appears in approximately 15% of education-focused sources, disproportionately from non-Anglophone contexts.

[21] When artificial intelligence substitutes humans in higher education: the cost of loneliness, student success, and retention

[1] "Chat GPT y sedentarismo cognitivo: aprender de consultas a la IA ...

**Causal attribution:** Success attribution in our corpus favors institutional factors—clear policies, faculty development programs,

technology infrastructure. [5] attributes positive outcomes to pedagogical design choices rather than student characteristics. Failure attribution, by contrast, often individualizes—positioning problems as faculty resistance or student misuse. This asymmetry matters: it suggests institutions claim credit for success while distributing blame for failure.

[5] From Intimidation to Innovation: Cross-Continental Multiple Case Studies on How to Harness AI to Elevate Engagement, Comprehension, and Retention

### *Failure Pattern Analysis*

Documented failures in our corpus cluster into three categories. **Detection failures** appear most prominently: [10] and [18] document the unreliability of AI detection tools and the legal complexities of defining AI-assisted work as plagiarism. False positives generate student grievances; false negatives undermine assessment validity.

[10] How college professors are adapting to rampant AI cheating

[18] Plagiarism Copyright and Ai

**Implementation failures** center on pace mismatches—policies preceding training, technology deployment preceding pedagogical preparation. [14] catalogues implementation gaps across institutions. **Pedagogical failures**—cases where AI integration demonstrably harmed learning—appear underreported, though [22] raises questions about writing skill development that remain empirically unresolved.

[14] Navigating the Complexity of Generative Artificial Intelligence in Higher Education: A Systematic Literature Review

[22] Writing with machines? Reconceptualizing student work in the age of AI

### *Research Gaps Affecting Decisions*

Critical absences in our evidence base constrain actionable guidance. **Longitudinal learning outcomes**: we found no studies tracking cohorts through multi-year AI-integrated curricula. Faculty cannot know whether current approaches build or erode capabilities over time. **Disciplinary variation**: most sources generalize across fields; whether AI integration differs for philosophy versus engineering versus nursing remains underexamined. [12] represents rare disciplinary specificity.

[12] Literature Review on the Integration of Generative AI in Programming ...

**Accessibility interactions**: [20] begins addressing how AI intersects with accessibility frameworks, but evidence remains preliminary. We cannot confidently advise on whether AI tools expand or contract access for students with disabilities.

[20] UNIVERSAL DESIGN FOR LEARNING, ACCESSIBLE LEARNING DESIGN AND ARTIFICIAL INTELLIGENCE: AN EXPLORATORY STUDY ON PRE-SERVICE TEACHERS

### *Secondary Tensions*

Beyond the core detection-versus-design tension, our analysis identifies intersecting contradictions. The *standardization-versus-autonomy* tension surfaces in policy documents: institutions want consistent approaches, but [8] acknowledges disciplinary autonomy matters. The *transparency-versus-protection* tension appears in [11]—surveillance tools for academic integrity raise privacy concerns. These secondary tensions lack the extensive documentation of the primary contradiction but will likely surface in implementation.

[8] Generative Artificial Intelligence in Teaching and Learning at McMaster University

[11] La AEPD sanciona el tratamiento de datos biométricos con IA en la ...

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