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Research Article

# Cultural and Digital Readiness for AI-Integrated Higher Education: A C-TAM-Informed Curriculum Design Framework

Jeremy Bennett[1,*]
[1]Oglethorpe University, Atlanta 30319, United States
[*]**Correspondence:** Jeremy Bennett, jbennettphd@gmail.com

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## Abstract

Generative artificial intelligence (GenAI) requires higher education institutions to redesign curricula, assessments, and student support rather than merely authorize or prohibit a new tool. This article develops a Cultural-Technology Acceptance Model (C-TAM) as a theory-building curriculum framework. It integrates current studies of university students' GenAI use with established technology-acceptance research, cross-cultural scholarship, AI-literacy frameworks, backward design, constructive alignment, and assessment reform. The revision explicitly limits the role of pre-GenAI evidence. Programme for International Student Assessment (PISA) 2018 and World Values Survey (WVS) Wave 7 indicators are treated as contextual evidence about the digital and cultural readiness pipeline entering higher education; they are not treated as measures of GenAI acceptance, and no cross-national structural equation model is estimated from them. The synthesis identifies five mechanisms that curriculum designers should anticipate: perceived usefulness, perceived ease of use and AI competence, attitudes shaped by trust and ethical risk, social and institutional norms, and culturally patterned expectations about uncertainty and authority. These mechanisms are translated through backward design into aligned learning outcomes, assessment evidence, pedagogy, and support. An AI-Ready Curriculum Reconstruction Matrix specifies adaptations for students who combine high uncertainty avoidance with high power-distance expectations, including explicit permissions, low-stakes rehearsal, modelled verification, multiple participation routes, process evidence, and equitable access. The article contributes a bounded and testable framework for culturally responsive AI integration while providing a transparent protocol for future direct, multilevel, cross-cultural validation.

**Keywords**

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Generative AI, Curriculum design, AI literacy, Culturally responsive pedagogy, Technology acceptance, Assessment reform, Digital readiness, Higher education

## 1. Introduction

Generative artificial intelligence has moved rapidly into the ordinary work of higher education. Students use GenAI systems to brainstorm, explain concepts, translate text, produce code, revise prose, and simulate feedback, while instructors use similar systems to create examples, plan lessons, and redesign assignments. These practices create opportunities for learning, but they also intensify concerns about accuracy, privacy, bias, authorship, overreliance, and unequal access (Crompton & Burke, 2023; Miao & Holmes, 2023; UNESCO, 2024). The curriculum problem is therefore not simply whether GenAI should be allowed. It is how learning outcomes, assessments, pedagogy, and student support should be redesigned so that AI use strengthens rather than displaces disciplinary knowledge, judgment, creativity, and accountability.

Current student research shows that GenAI use is already heterogeneous. University students often recognize substantial utility, yet their use differs by discipline, prior experience, institutional policy, and perceived ethical risk (Baek et al., 2024; Johnston et al., 2024). Acceptance studies likewise find that performance expectancy or perceived usefulness, facilitating conditions, attitudes, and AI competence help explain intention and actual use (Delcker et al., 2024; Strzelecki, 2024). These findings make technology acceptance relevant to curriculum design, but the distinctive properties of GenAI require more than a direct transfer of models developed for conventional information systems. GenAI produces content, responds probabilistically, can conceal errors behind fluent language, and raises assignment-specific questions about acceptable assistance and evidence of learning (Lodge et al., 2023; Miao & Holmes, 2023).

The challenge is especially important in culturally and linguistically diverse institutions. Students may differ in their comfort with ambiguity, expectations of instructor authority, willingness to experiment without explicit permission, and interpretations of collaboration or assistance. Cross-cultural technology research suggests that social influence and espoused cultural values can shape adoption, although these relationships are probabilistic rather than deterministic and should not be reduced to national stereotypes (Srite & Karahanna, 2006; Tarhini et al., 2015; Yoo et al., 2011). For curriculum designers, the practical question is not whether a student belongs to a fixed cultural type. It is whether the course provides enough clarity, autonomy, support, and access for students with different expectations to participate equitably.

This article develops a Cultural-Technology Acceptance Model (C-TAM) as a curriculum design framework. The Technology Acceptance Model (TAM) proposes that perceived usefulness and

perceived ease of use shape attitudes and behavioral intentions toward a technology (Davis, 1989). C-TAM retains these mechanisms but places them within social, cultural, ethical, and institutional conditions relevant to GenAI-mediated learning. The model is then connected to backward design and constructive alignment, which organize curriculum planning around desired outcomes, acceptable evidence, and aligned learning experiences (Biggs & Tang, 2011; Wiggins & McTighe, 2005).

The revised article makes a deliberate evidentiary distinction. PISA 2018 predates the public diffusion of ChatGPT and sampled 15-year-old students; WVS Wave 7 measures broad values rather than classroom behavior. These sources cannot directly measure GenAI acceptance among university students. They are used only as contextual evidence about the digital confidence, access, uncertainty, and authority expectations that may form part of the pipeline entering higher education (Haerpfer et al., 2022; OECD, 2019a, 2019b). Direct claims about contemporary GenAI use are grounded instead in post-2022 higher education studies. This boundary removes the earlier risk of relabeling pre-GenAI indicators as latent GenAI constructs.

The article addresses three questions: (1) Which acceptance, cultural, and ethical mechanisms are most consistently associated with university students' readiness to engage with GenAI? (2) How can those mechanisms be translated through backward design and constructive alignment into curriculum decisions? and (3) Which design adaptations promote equity for students who require greater certainty, explicit authorization, or access support? The contribution is a bounded, theory-building framework, a curriculum reconstruction matrix, and a transparent protocol for future direct cross-cultural testing.

## 2. Literature Review

### 2.1. From technology acceptance to GenAI readiness

TAM explains technology adoption through two core beliefs: perceived usefulness, or the belief that a system will improve performance, and perceived ease of use, or the belief that using it will require manageable effort (Davis, 1989; Bennett & Bennett, 2026). Meta-analytic evidence in education supports the continuing importance of these constructs, while extensions such as UTAUT add social influence and facilitating conditions (Scherer et al., 2019; Venkatesh et al., 2003). In curriculum terms, usefulness is not an inherent property of an AI system. It depends on whether the course connects the tool to a legitimate learning purpose. Ease of use also extends beyond interface simplicity to include access, prompting knowledge, verification skill, and confidence about what the instructor permits.

Direct studies of GenAI in higher education support this expanded view. Strzelecki (2024) found that performance expectancy and related UTAUT mechanisms predicted students' intentions to use ChatGPT. Delcker et al. (2024) linked AI competence and attitudes to intended and actual use among first-year students. Baek et al. (2024) showed that U.S. college students' use varied across tasks and

student characteristics, while Johnston et al. (2024) documented a strong demand for institution-wide clarity about appropriate use. Together, these studies indicate that adoption is simultaneously functional, social, and regulatory.

GenAI nevertheless differs from many technologies used in earlier acceptance research. It creates original-seeming outputs, varies across prompts and model versions, and can produce inaccurate or fabricated information. Students must therefore judge not only whether a system is useful and usable but also whether its outputs are trustworthy, whether use is ethically permissible, and whether the learning process remains visible. This article uses the term GenAI readiness to capture the combination of intention, competence, critical judgment, and contextual permission required for responsible educational use.

## 2.2. A limited digital and cultural readiness pipeline

Pre-GenAI digital evidence can inform curriculum planning only within strict limits. PISA 2018 includes internationally developed measures of students' access to and familiarity with information and communication technologies, attitudes toward digital activities, and school contexts (OECD, 2019a, 2019b). The WVS measures broad values related to authority, autonomy, trust, and social expectations across societies (Haerpfer et al., 2022). Such evidence may help institutions anticipate uneven prior exposure and culturally patterned expectations among future entrants. It cannot establish whether contemporary university students will use ChatGPT, whether they trust generated content, or whether they consider a particular use academically ethical.

The proxy logic is therefore antecedent rather than substitutive. General digital confidence may reduce the initial effort required to learn an AI interface; prior access may influence whether students arrive with informal prompting experience; and broader uncertainty or authority expectations may shape reactions to ambiguous policies. Current direct studies provide some support for these pathways because AI competence, facilitating conditions, policy clarity, and perceived risk are associated with use and acceptance (Baek et al., 2024; Delcker et al., 2024; Johnston et al., 2024). However, a pre-2022 digital indicator is not a validated measure of a post-2022 GenAI construct. Table 1 states the permissible and impermissible uses of each evidence source.

A second boundary concerns population. Fifteen-year-old PISA participants learn in more regulated settings than university students, and their responses should not be extrapolated directly to autonomous higher education environments. Their relevance is developmental and institutional: many members of the PISA 2018 cohort have since entered or are approaching higher education, bringing uneven digital experiences with them. The pipeline concept therefore supports questions about transition and support, not causal claims about university behavior.

**Table 1**

*Evidentiary Boundaries for the Digital and Cultural Readiness Pipeline*

| Evidence source | What it can inform | What it cannot establish | Use in this article |
|---|---|---|---|
| Post-2022 university GenAI studies | Current intentions, use, perceived benefits, risks, competence, and policy expectations | Universal or culturally invariant effects without appropriate comparative designs | Primary evidence for contemporary GenAI mechanisms |
| PISA 2018 ICT and school-context measures | Uneven prior digital access, familiarity, confidence, and institutional exposure among a secondary-school cohort | Direct GenAI acceptance, university behavior, or GenAI-specific ethics and trust | Contextual pipeline evidence only |
| WVS Wave 7 | Broad distributions of values concerning authority, autonomy, trust, and uncertainty | Individual student behavior or course-level causal effects | Context for culturally responsive design questions |
| Hofstede-informed cultural constructs | Theory about possible differences in authority, uncertainty, individualism, and future orientation | Fixed national traits or valid individual scores assigned from country averages | Heuristic concepts; direct testing requires individual-level measures |

## 2.3. Culture, social influence, and non-deterministic design

Cross-cultural technology studies show that adoption mechanisms can vary across settings. Social influence may be more consequential where authority and group expectations are salient, while uncertainty avoidance may make ambiguous or rapidly changing technologies more difficult to approach (Srite & Karahanna, 2006; Tarhini et al., 2015). Individual-level cultural value scales are preferable to assigning national averages to individuals because national dimensions describe central tendencies and can obscure within-country heterogeneity (Yoo et al., 2011). Culture should therefore be treated as a source of hypotheses and design sensitivities, not a label that predicts a student's behavior.

For GenAI curricula, power distance is most useful as an expectation about authorization. Students who expect strong instructional authority may wait for explicit permission, interpret silence as prohibition, or hesitate to challenge an AI output that appears authoritative. Uncertainty avoidance is relevant because GenAI policies and outputs are often ambiguous. Long-term orientation may increase interest when AI literacy is connected to professional preparation, while collectivist orientations may make peer norms and collaborative learning especially influential. Each mechanism suggests a course-design response rather than a cultural judgment.

Culturally responsive pedagogy reinforces this orientation by asking educators to connect instruction to varied experiences while maintaining rigorous learning goals (Gay, 2018;

Ladson-Billings, 1995). The objective is not to create separate curricula for national groups. It is to provide multiple, transparent routes into the same outcomes: explicit rules for students who need certainty, meaningful autonomy for students ready to explore, collaborative and individual practice, and access arrangements that do not assume prior subscription to commercial tools.

### 2.4. Curriculum theory, AI literacy, and assessment reform

Backward design is a three-stage curriculum framework. Designers first specify the enduring learning outcomes, then identify acceptable evidence that students have achieved those outcomes, and only then plan learning activities and instruction (Wiggins & McTighe, 2005). Constructive alignment similarly requires consistency among outcomes, teaching activities, and assessment criteria (Biggs & Tang, 2011). GenAI makes this alignment visible. When an outcome requires independent recall or unaided performance, AI use may be restricted. When an outcome requires critical use of professional tools, AI-assisted work may be necessary, but students should still demonstrate verification, reasoning, and accountability.

AI literacy expands the desired outcomes beyond operational prompting. UNESCO's student competency framework organizes AI learning around a human-centered mindset, ethics, techniques and applications, and system design (UNESCO, 2024). Guidance for GenAI in education likewise emphasizes privacy, age appropriateness, human agency, and validation of outputs (Miao & Holmes, 2023). These frameworks support outcomes such as explaining model limitations, identifying bias, verifying claims, documenting assistance, protecting sensitive data, and deciding when not to use AI.

Assessment reform is equally central. Process evidence—such as annotated prompts, source checks, oral defenses, drafts, decision logs, and reflective explanations—can make students' judgment visible without relying on unreliable AI detection. Authentic assessment asks students to complete meaningful disciplinary or professional tasks, while long-term learning requires assessment that prepares students to judge their own future work (Boud & Falchikov, 2006). Recent higher education guidance recommends redesigning assessment regimes so institutions can assure learning in environments where GenAI is widely available (Lodge et al., 2023). These principles provide the curriculum architecture through which C-TAM mechanisms become actionable.

## 3. C-TAM Readiness Framework and Propositions

C-TAM is a curriculum-facing extension of technology acceptance theory. It does not claim that cultural dimensions replace usefulness and ease of use. Instead, it specifies conditions under which students interpret usefulness, effort, risk, and social permission. The framework also adds GenAI-specific trust and ethics because a system that generates content creates risks that conventional platform acceptance models do not fully represent. The following propositions are intended for direct

testing with current higher education samples; they are not presented as results from PISA or WVS data.

**Table 2**

*Structured C-TAM Propositions and Curriculum Mechanisms*

| Proposition | Testable relationship | Primary curriculum lever |
|---|---|---|
| P1 | When GenAI activities are visibly connected to course and professional learning outcomes, perceived usefulness will be positively associated with responsible intention to use GenAI. | Outcome transparency and authentic disciplinary tasks |
| P2 | AI competence, accessible tools, and scaffolded practice will reduce perceived effort and strengthen responsible intention and use. | Scaffolding, access, and guided practice |
| P3 | Trust calibrated through verification practice—and ethical clarity about acceptable use—will strengthen positive attitudes more than unqualified encouragement to use GenAI. | Verification routines, ethical cases, and documentation |
| P4 | Instructor, peer, and institutional norms will have stronger effects when students perceive greater authority distance or depend on explicit authorization. | Explicit instructor and institutional norm setting |
| P5 | Uncertainty avoidance will be associated with lower willingness to experiment under ambiguous policies, but this relationship will weaken when courses provide exemplars, decision rules, and low-stakes rehearsal. | Clear permissions, exemplars, decision trees, and rehearsal |
| P6 | Long-term professional relevance will strengthen perceived usefulness, while equitable access and culturally responsive support will reduce participation gaps across student groups. | Career relevance, universal design, and equitable tool access |

# 4. Method

## 4.1. Design

The revised study uses a theory-building integrative evidence synthesis. Its purpose is to connect three bodies of scholarship that are often treated separately: (a) direct post-2022 studies of GenAI acceptance and use in higher education, (b) established technology-acceptance and cross-cultural research, and (c) curriculum, assessment, and AI-literacy frameworks. The approach is interpretive and design-oriented rather than a meta-analysis or a new secondary-data SEM. Accordingly, the article reports no newly estimated path coefficients, model-fit indices, or cross-national latent mean comparisons.

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The change in design responds directly to the temporal and measurement limitations of the retained source files. The original manuscript referred to an SEM using PISA 2018, WVS Wave 7, and Hofstede indicators, but the item-level analytic dataset, code, country composition, weights, and construct mappings were not available for reproducible reanalysis. More importantly, pre-GenAI items cannot be relabeled as direct measures of GenAI acceptance. Rather than retain unsupported estimates or fabricate missing validation statistics, the revision removes those claims and uses the older sources only to define contextual readiness questions.

## 4.2. Evidence sources and inclusion logic

Direct evidence was drawn from peer-reviewed higher education studies published after the public diffusion of ChatGPT that examined student use, intentions, competence, benefits, risks, or policy expectations. Representative studies were selected to provide variation in method and setting, including UTAUT-based acceptance modeling, path analysis of AI competence and use, large-scale U.S. survey evidence, and institutional policy-focused student research (Baek et al., 2024; Delcker et al., 2024; Johnston et al., 2024; Strzelecki, 2024). The synthesis also included international guidance and assessment reform sources with explicit implications for learning outcomes and evidence of learning (Lodge et al., 2023; Miao & Holmes, 2023; UNESCO, 2024).

Established theory sources were included when they defined a construct used in the framework or provided evidence about its educational or cross-cultural operation. These sources include TAM and UTAUT, educational technology meta-analysis, espoused cultural values in technology acceptance, culturally responsive pedagogy, backward design, constructive alignment, and learning-oriented assessment (Biggs & Tang, 2011; Boud & Falchikov, 2006; Davis, 1989; Gay, 2018; Scherer et al., 2019; Srite & Karahanna, 2006; Venkatesh et al., 2003; Wiggins & McTighe, 2005).

PISA 2018 and WVS Wave 7 were retained only because they were central to the manuscript's original framing. The OECD documentation was used to identify the intended scope of PISA measures, and the WVS documentation was used to characterize its broad value indicators (Haerpfer et al., 2022; OECD, 2019a, 2019b). No individual PISA or WVS response was recoded as a GenAI variable, and no person-level cultural value was inferred from a national Hofstede score.

## 4.3. Analytic synthesis procedure

The synthesis proceeded in four steps. First, each evidence source was classified as direct GenAI evidence, established acceptance/cultural theory, curriculum and assessment theory, or contextual readiness evidence. Second, reported constructs were mapped to six C-TAM domains: usefulness, ease/competence, attitude/trust, social norms, uncertainty/authority expectations, and facilitating/equity conditions. Third, each domain was translated through the three stages of backward design: desired outcomes, acceptable assessment evidence, and pedagogy/support. Fourth, the

resulting design principles were stress-tested against the combined condition emphasized by the reviewers—high uncertainty avoidance and high power-distance expectations—to determine whether the same learning outcomes could be reached through more explicit and equitable scaffolding.

The analysis sought convergence rather than numerical aggregation. A mechanism was retained when it appeared in established acceptance theory and was also supported or problematized by contemporary higher education evidence. Divergence was recorded when GenAI added a concern that conventional technology models did not capture, particularly trust, academic ethics, output verification, authorship, and unequal access.

### 4.4. Measurement validity and future cross-cultural testing

Because no cross-cultural latent-variable model is estimated in this revision, measurement invariance is not assumed. This is a substantive safeguard rather than a missing statistical step. Comparing latent means or structural paths across groups requires evidence of configural and metric invariance and, for mean comparisons, scalar invariance (Putnick & Bornstein, 2016). Direct future testing should also distinguish student-level espoused values from country-level indicators and account for nesting within courses, institutions, and countries.

Appendix B provides a complete validation protocol for a future C-TAM study. It specifies item provenance, translation procedures, pilot cognitive interviews, factor loadings, composite reliability, average variance extracted, discriminant validity, configural/metric/scalar invariance, multilevel modeling, survey weights where applicable, missing-data treatment, and transparent reporting of coefficients, uncertainty intervals, and code. This protocol replaces the unverifiable fit statistics and adapted coefficients that appeared in the original manuscript.

## 5. Findings from the Integrative Synthesis

### 5.1. Usefulness must be designed, not assumed

Across acceptance theory and current GenAI studies, usefulness remains the most stable mechanism. Students are more likely to intend to use an AI system when they expect it to improve performance, efficiency, or learning (Davis, 1989; Strzelecki, 2024). Yet Baek et al. (2024) show that use differs across writing, programming, and general tasks, indicating that usefulness is assignment-specific. Curriculum designers therefore create perceived usefulness when they connect AI activity to disciplinary judgment rather than presenting generic prompting as an end in itself.

The design implication is to state why AI is present. A statistics course might use GenAI to critique an interpretation rather than calculate a result; a writing course might compare rhetorical alternatives while preserving source-based authorship; a management course might test strategic

assumptions against evidence. In each case, the outcome should identify the human capability that remains accountable.

## 5.2. Ease of use includes competence, access, and policy clarity

Ease of use in GenAI settings is not limited to interface convenience. Delcker et al. (2024) show that AI competence is related to intended and actual use, and current student evidence indicates that institutional rules influence participation (Baek et al., 2024; Johnston et al., 2024). Students who lack paid access, reliable devices, language confidence, or experience verifying outputs face higher effective effort even when a chatbot appears simple.

Scaffolding should therefore include a common-access tool or non-tool alternative, model prompts, examples of weak and strong verification, low-stakes rehearsal, and clear data-protection rules. These supports improve inclusion without lowering the learning standard.

## 5.3. Attitudes depend on calibrated trust and ethical legitimacy

Conventional acceptance models often treat attitude as a general favorable or unfavorable evaluation. GenAI attitudes are more conditional. Students may value speed while distrusting accuracy, or welcome language support while worrying about authorship and academic integrity (Johnston et al., 2024; Miao & Holmes, 2023). Positive attitude should therefore not be equated with uncritical use.

The curriculum goal is calibrated trust: students should know when an output is plausible, when external verification is required, and when a task should remain human-only. Assessment can make this judgment visible through source audits, error analyses, prompt and revision logs, or oral explanations of what was accepted, changed, and rejected.

## 5.4. Social and institutional norms are part of the curriculum

Student uncertainty is amplified when instructors, departments, and institutions send conflicting signals. Johnston et al. (2024) found substantial student support for university-wide guidance, while Baek et al. (2024) identified institutional policy as one factor associated with use. Social influence is therefore not external to curriculum design; it is communicated through syllabi, assignment instructions, classroom modeling, peer examples, and assessment consequences.

A single institution-wide principle cannot replace assignment-level direction. Students need to know whether a specific task permits no AI, AI for specified support, or full AI integration with documentation. Faculty modeling is especially important for students who are reluctant to act without explicit authorization.

## 5.5. Culture shapes interpretation, not capability

The cross-cultural literature suggests that uncertainty and authority expectations can moderate responses to new technologies (Srite & Karahanna, 2006; Tarhini et al., 2015). The synthesis does not establish that a particular national group will accept or reject GenAI. Instead, it identifies predictable design failures: vague rules disadvantage students who need certainty, silent instructor norms disadvantage students who seek authorization, exclusively individual experimentation may disadvantage students who learn through guided or collaborative practice, and paid-tool assumptions disadvantage students with limited resources.

Culturally responsive design treats these differences as requirements for clarity and choice. It makes permissions explicit, uses examples that reveal disciplinary expectations, invites questions without penalty, and offers both collaborative and independent routes to practice.

**Table 3**

*Comparison of Contemporary Higher Education Evidence with C-TAM Mechanisms*

| Study | Setting and design | Relevant evidence | C-TAM interpretation |
|---|---|---|---|
| Strzelecki (2024) | 503 higher education students; extended UTAUT | Performance expectancy and related acceptance mechanisms predict intention/use | Usefulness remains central but requires GenAI-specific extension |
| Delcker et al. (2024) | 634 first-year students; AI competence and path analysis | Competence and attitudes relate to intended and actual AI-tool use | Ease includes knowledge, skills, confidence, and facilitating conditions |
| Baek et al. (2024) | 1,001 U.S. college students; survey/regression | Use varies by task, student characteristics, and institutional policy | Usefulness and norms are contextual; access and equity matter |
| Johnston et al. (2024) | University student survey focused on integrity policy | Students report benefits and concerns and seek clearer institutional rules | Ethical legitimacy and explicit norms shape readiness |
| UNESCO (2024); Lodge et al. (2023) | International competency and assessment guidance | Human-centered ethics, critical evaluation, and assurance of learning | Curriculum must align outcomes, process evidence, and safeguards |

## 6. Discussion

The synthesis supports the continuing relevance of acceptance theory while clarifying where GenAI requires a curriculum-specific extension. Consistent with Davis (1989), Scherer et al. (2019), and Strzelecki (2024), students need to perceive educational value. Consistent with UTAUT and

Delcker et al. (2024), facilitating conditions and competence affect whether intention becomes use. The current evidence, however, extends these models because GenAI adoption depends on ethical permission, calibrated trust, and visible evidence of learning. These are not peripheral concerns: they determine whether a nominally useful tool is educationally legitimate in a particular assignment.

The findings also refine the role of culture. Earlier cross-cultural acceptance research often tested national or individual cultural values as moderators of adoption pathways (Srite & Karahanna, 2006; Tarhini et al., 2015). For curriculum design, the more useful move is to ask how varying expectations about uncertainty and authority interact with course signals. A student's reluctance under an ambiguous policy may reflect rational uncertainty rather than low technological ability. Providing explicit examples and safe rehearsal can therefore alter the context in which an acceptance relationship operates.

This interpretation differs sharply from the original manuscript's empirical framing. PISA 2018 does not measure ChatGPT acceptance, and WVS or country-level Hofstede indicators cannot validate person-level GenAI pathways. OECD scale validation establishes the intended measurement properties of PISA constructs within the PISA framework, not their validity after relabeling as TAM or GenAI constructs (OECD, 2019a, 2019b). By removing the unsupported SEM and separating contextual from direct evidence, the revised argument becomes narrower but more credible.

The synthesis also supports a stronger dialogue with curriculum theory. Backward design prevents institutions from beginning with the tool. The first question is which learning remains valuable; the second is what evidence can demonstrate that learning; the third is which AI-enabled or AI-restricted activities can produce that evidence. Constructive alignment then checks that the stated AI policy, learning activities, and grading criteria do not contradict one another. Assessment reform contributes process evidence and authentic tasks, while culturally responsive pedagogy ensures that clarity and access are not mistaken for lowered rigor.

The framework should be understood as a set of testable mechanisms, not a finished causal model. Direct cross-cultural validation remains necessary. A strong future study would collect current GenAI-specific measures from university students, use individual-level cultural value items, test measurement invariance, and model students within courses and institutions. The present contribution is to specify what such a study should measure and how its findings could be translated into curriculum decisions.

# 7. Implications for AI-Ready Curriculum Design

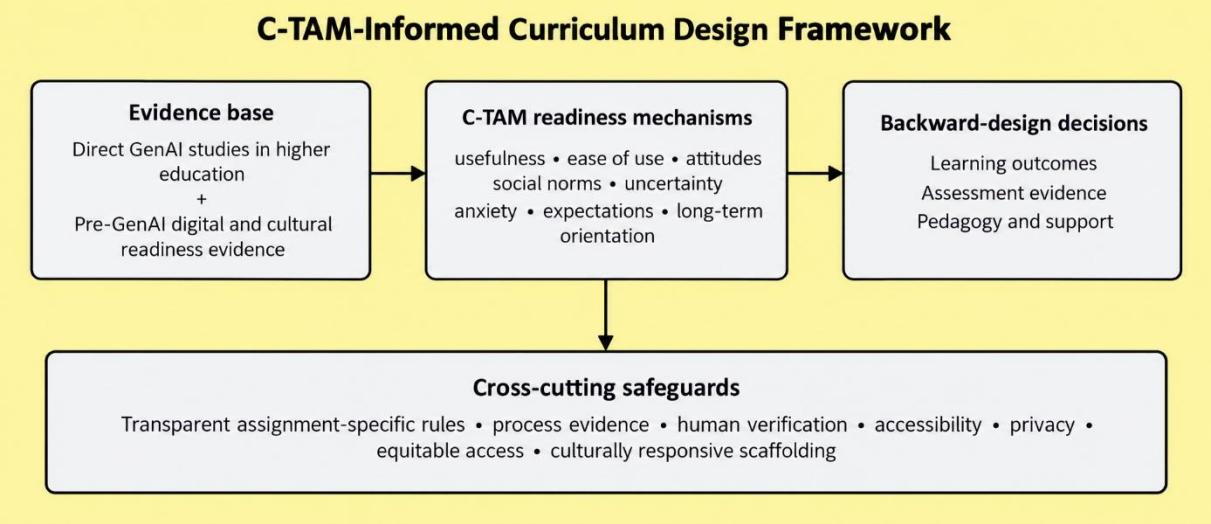
## 7.1. Backward design and constructive alignment

Figure 1 links the revised evidence base to C-TAM readiness mechanisms and then to the three stages of backward design. The arrows are directional but not causal estimates. They show the design

sequence: interpret evidence cautiously, identify the mechanism likely to affect participation, and select aligned outcomes, assessment evidence, pedagogy, and support. Equity and inclusion safeguards operate across all stages.

**Figure 1**

*C-TAM-Informed Curriculum Design Framework*




Stage 1—Desired outcomes. Courses should identify both disciplinary outcomes and the AI literacy required to achieve them responsibly. Appropriate outcomes may include explaining model limitations, determining when AI use is warranted, verifying generated claims, documenting assistance, protecting confidential information, and retaining human accountability. Outcomes should avoid generic statements such as “use AI effectively” unless effectiveness is defined through disciplinary criteria.

Stage 2—Assessment evidence. Evidence should match the outcome and the permitted role of AI. Where independent performance is essential, an oral, in-class, or supervised component may be appropriate. Where AI-assisted practice is authentic, assessment should examine judgment through annotated outputs, source checks, decision logs, comparative drafts, or oral defense. The goal is assurance of learning rather than surveillance of tool use.

Stage 3—Pedagogy and support. Students need guided practice before high-stakes assessment. Instructors should model acceptable and unacceptable uses, demonstrate verification, discuss ethical edge cases, and provide common access or a pedagogically equivalent alternative. Support should be designed for varied prior digital experience and cultural expectations, not offered only after students fail.

## 7.2. AI-Ready Curriculum Reconstruction Matrix

Table 4 translates the framework into concrete curriculum choices. The high-uncertainty-avoidance plus high-power-distance column directly addresses the population most

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likely to be disadvantaged by ambiguous permission and unspoken expectations. The adaptations preserve common outcomes and standards while changing the route by which students gain confidence and demonstrate learning.

**Table 4**

*AI-Ready Curriculum Reconstruction Comparison Matrix*

| Backward-design element | Baseline AI-ready design | Adaptation for high uncertainty avoidance + high power-distance expectations | Equity and inclusion safeguard |
|---|---|---|---|
| Learning outcomes | Define disciplinary judgment, AI literacy, ethical use, and human accountability | State what students must decide independently; distinguish required, optional, and prohibited AI uses; connect each rule to the learning purpose | Use plain language, accessible formats, and examples relevant across disciplines and linguistic backgrounds |
| Assignment instructions | Use a three-level permission label: no AI; limited/supportive AI; integrated AI with disclosure | Provide a decision tree, worked examples, and instructor confirmation; avoid relying on "use your judgment" without criteria | Offer a confidential channel for questions and permit clarification without penalty |
| Low-stakes practice | Practice prompting, critique, verification, and revision before graded work | Begin with instructor-modeled demonstrations and guided group rehearsal before individual experimentation | Provide institutionally available tools or a no-cost equivalent task |
| Assessment evidence | Require products plus process evidence appropriate to the outcome | Specify exactly which artifacts count: prompt excerpts, source checks, decision notes, or oral explanation; show an exemplar | Allow multiple evidence formats where they assess the same outcome and accommodate disability/access needs |
| Feedback | Evaluate disciplinary reasoning, accuracy, transparency, and ethical choices | Use rubric language that explicitly rewards verification and explains consequences of unverified AI claims | Separate language fluency from disciplinary quality when appropriate; provide formative feedback before sanctions |
| Participation and collaboration | Combine individual judgment with peer critique and collaborative calibration | Use structured roles and instructor-facilitated discussion before expecting public disagreement with peers or AI outputs | Avoid participation designs that privilege confidence, native-language fluency, or prior AI access |
| Academic integrity | Define acceptable assistance at assignment level and require proportionate disclosure | Explain grey areas with contrasting cases; distinguish misuse from good-faith error during early practice | Use educative responses and revision opportunities for minor first-time misunderstandings |

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| | | | |
|---|---|---|---|
| Career relevance | Connect AI use to professional standards and long-term learning | Make the future value explicit and include profession-specific accountability scenarios | Include critical discussion of labor, bias, privacy, environmental costs, and who benefits from automation |

### 7.3. Assignment-level policy template

A practical implementation tool is a short policy block embedded in every major assignment rather than a single syllabus statement. The block should specify: (a) the learning purpose; (b) the permitted level of AI assistance; (c) prohibited uses; (d) required disclosure or process evidence; (e) verification expectations; (f) privacy restrictions; and (g) access alternatives. Appendix C provides a template. Repetition across assignments reduces ambiguity while preserving instructor flexibility.

## 8. Limitations and Future Research

This article is a theory-building integrative synthesis, not a systematic review or new empirical test. The selected contemporary studies illustrate convergent mechanisms but do not exhaust the rapidly expanding GenAI literature. Their samples, institutions, countries, and outcome measures differ, so the synthesis cannot estimate an average effect or rank cultural predictors.

The PISA and WVS sources remain temporally and substantively limited. PISA 2018 participants were 15-year-olds in secondary education, and its digital measures predate widespread GenAI. WVS values are broad and are not course-level behaviors. These sources support only contextual questions about the readiness pipeline. They do not support direct inferences about university students, faculty, or GenAI adoption.

No new N=200–300 survey or focus-group study was added. Collecting a convenience sample solely to satisfy revision timing would not solve the central validity problem unless the instrument, sampling plan, and cross-cultural measurement strategy were designed prospectively. The revision instead strengthens the direct post-2022 evidence base and specifies a rigorous future protocol. A subsequent study should recruit current university students across multiple institutions and countries, measure actual use by task, include GenAI-specific trust and ethics, and collect individual-level cultural orientations.

Future empirical work should report item wording and provenance, cognitive-interview results, missing-data treatment, factor loadings, composite reliability, average variance extracted, discriminant validity, and configural, metric, and scalar invariance. Multilevel models should distinguish student, course, institution, and country effects; survey weights should be used when the sampling design requires them. Pre-registration, open code, and de-identified data or a justified access procedure would further improve reproducibility. Appendix B presents the full checklist.

Finally, cultural responsiveness should be evaluated through outcomes rather than assumed from design intent. Studies should test whether clearer permissions, structured rehearsal, and equitable access reduce gaps in participation, confidence, learning, and academic-integrity misunderstandings without suppressing student autonomy.

## 9. Conclusion

GenAI integration is a curriculum design problem before it is a technology adoption problem. Acceptance mechanisms matter because students cannot benefit from a learning activity they do not understand, trust, or believe they are permitted to attempt. Yet increasing use is not the objective. The objective is responsible participation that strengthens disciplinary learning and preserves human judgment.

The revised C-TAM framework connects usefulness, ease and competence, calibrated trust, social norms, and culturally patterned expectations to backward-design decisions about outcomes, assessment evidence, pedagogy, and support. It also establishes clear evidentiary boundaries: current GenAI claims require current GenAI data, while PISA and WVS can provide only contextual readiness evidence. This narrower framing removes unsupported causal and cross-cultural claims while producing a more actionable curriculum contribution.

AI-ready curricula should therefore make purposes and permissions explicit, provide low-stakes practice, assess process and judgment, model verification, protect privacy, and ensure equitable access. These practices are particularly important for students who are uncomfortable with ambiguity or reluctant to proceed without clear instructor authorization. The framework and appendices offer a transparent foundation for direct future validation and for immediate, culturally responsive curriculum redesign.

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### Author contributions

Jeremy Bennett contributed to all areas.

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### Data availability

No new human-subjects data were collected and no new statistical analysis was conducted for this revision. PISA 2018 and WVS Wave 7 are publicly documented sources used only for contextual

discussion. The original item-level analytic dataset and code referenced in the prior manuscript were not available in the retained submission files; consequently, the revised article removes the earlier SEM estimates and does not report unreproducible measurement or structural results. The evidence-source boundaries and future validation requirements are documented in Tables 1–3 and Appendices A–B.

## Declarations

### Conflict of interest

No Conflicts of Interest.

### Ethics approval

Not applicable.

### Consent to participate

Not applicable.

### Consent for publication

Not applicable.

## Additional information

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## Appendix A

## Evidence-Source and Construct Audit

This appendix documents how each evidence class is used and prevents construct relabeling across sources.

**Table A1**

*Construct Audit*

| C-TAM domain | Direct contemporary indicator needed for empirical testing | Contextual antecedent that may be studied separately | Curriculum decision informed |
|---|---|---|---|
| Perceived usefulness | GenAI task-specific performance expectancy or learning value | General attitudes toward educational technology | Connect AI to authentic disciplinary outcomes |
| Ease/competence | GenAI skills, confidence, access, prompting, and verification ability | Prior ICT familiarity and access | Provide scaffolding, common access, and alternatives |
| Attitude/trust | GenAI-specific trust, risk, ethical legitimacy, and affect | General technology attitudes | Teach calibrated trust and ethical decision-making |
| Social norms | Instructor, peer, institutional, and professional expectations for the specific task | Broad authority or conformity values | Use explicit assignment-level permissions and modeling |
| Uncertainty/authority expectations | Individual-level espoused cultural values and policy ambiguity perceptions | Country or cohort context | Offer decision rules, examples, safe rehearsal, and question channels |
| Responsible use | Actual task behavior, disclosure, verification, and learning evidence | None; cannot be inferred from pre-GenAI data | Assess process, judgment, and accountability |

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## Appendix B

### Protocol for Direct Cross-Cultural C-TAM Validation

A future empirical study should report the following elements before making cross-cultural comparisons or curriculum claims:

1. Sampling and levels: define the university population, countries, institutions, courses, disciplines, and recruitment process; distinguish students nested within courses, institutions, and countries; justify power at each level.
2. Current task-specific measures: measure actual and intended GenAI use by task, perceived usefulness, ease/competence, trust, ethical legitimacy, social norms, facilitating conditions, and learning outcomes. Do not substitute pre-GenAI digital items for GenAI constructs.
3. Cultural measurement: use individual-level espoused values, report within-country heterogeneity, and avoid assigning national scores to individual students. Record language and translation procedures.
4. Instrument development: provide item wording, source, response scale, adaptation rationale, expert review, cognitive interviews, pilot results, and evidence that the same construct meaning is plausible across groups.
5. Measurement model: report standardized factor loadings, item residuals, composite reliability, omega or alpha where appropriate, average variance extracted, factor correlations, and discriminant-validity evidence.
6. Measurement invariance: test configural, metric, and scalar invariance sequentially; report fit indices and changes using stated decision rules; consider partial invariance only with transparent theoretical justification.
7. Structural analysis: estimate direct, indirect, and moderated relationships only after adequate measurement evidence; report coefficients, standard errors, confidence intervals, exact p values, model fit, sensitivity tests, and alternative specifications.
8. Complex design and missing data: use survey weights and design variables when applicable; justify multilevel or cluster-robust estimation; describe missingness and use an appropriate method such as full-information maximum likelihood or multiple imputation.

9. Equity analysis: test whether access, disability, language background, first-generation status, discipline, and paid-tool availability influence participation or outcomes; avoid interpreting group differences as cultural deficits.
10. Reproducibility and ethics: preregister hypotheses where feasible, share de-identified data or an access protocol, publish code and a codebook, document model/version changes, protect confidential inputs, and obtain appropriate ethics review.

**Table B1**

*Minimum Statistical Reporting for C-TAM*

| Area | Required statistics or documentation | Decision supported |
|---|---|---|
| Measurement quality | Item loadings; CR; AVE; omega/alpha; factor correlations; discriminant validity | Whether constructs are measured reliably and distinctly |
| Cross-group equivalence | Configural, metric, scalar, and justified partial-invariance results | Whether paths or latent means may be compared |
| Structural results | Coefficients, SEs, CIs, exact p values, $R^2$, model fit, indirect/moderated effects | Whether propositions receive empirical support |
| Multilevel/design | ICC, cluster counts, weights, design effects, multilevel or robust specification | Whether uncertainty reflects the sampling structure |
| Robustness | Alternative codings, estimators, subgroup analyses, influential-case checks | Whether conclusions are sensitive to reasonable choices |

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## Appendix C

### Assignment-Specific GenAI Use Statement

Learning purpose: This assignment assesses [insert knowledge, skill, or judgment].

Permitted level: ☐ No GenAI ☐ Limited/supportive GenAI ☐ Integrated GenAI with documentation

Permitted uses: [for example, brainstorming, translation, feedback, coding support, or comparison].

Prohibited uses: [for example, generating the final response, uploading confidential data, or fabricating sources].

Required evidence: [for example, disclosure statement, selected prompt excerpts, source-verification table, revision notes, or oral explanation].

Verification expectation: You remain responsible for the accuracy, sources, reasoning, and final submission.

Access alternative: Students who cannot or prefer not to use the designated tool may complete [equivalent route] without academic penalty.

Questions and clarification: Ask through [channel]. Good-faith clarification before submission will not be penalized.