International Multidisciplinary Research Journal
ISSN: 2424-7073
Available Online at https://imrjournal.info/
Volume V; November 2026; Page No. 39-52
DOI: https://doi.org/10.47722/imrj.2001.90

Research Article

EMPOWERING EDUCATORS: USING THE C.O.D.E.S. FRAMEWORK TO DESIGN GENERATIVE AI USE STATEMENTS IN HIGHER EDUCATION

Jeralyne Manweiler

Instructional Facilitator and Educational Developer, Instructional and Leadership Development Centre, Learning and Teaching Division, Saskatchewan Polytechnic, Regina, Canada

ARTICLE INFO

Article History:

Received 15.07.2026
Accepted 15.10.2026
Published 30.11.2026

Keywords:

generative artificial intelligence, assessment design, academic integrity, transparency, instructional framework

ABSTRACT

Generative artificial intelligence (GenAI) has unsettled post-secondary assessment by raising questions about authorship, independent learner work, and assessment validity. Institutional policies and syllabus statements give general direction but seldom say how GenAI may be used in a particular assessment. This conceptual design paper introduces C.O.D.E.S., a framework written primarily for post-secondary instructors. Its five components ask instructors to Clarify the permitted level of GenAI use, offer instructional supports, define tools and purposes, Explain the rationale, and Set transparency and accountability expectations. The framework draws on backward design, adult learning principles, Transparency in Learning and Teaching, Universal Design for Learning, and reflective technology integration. It treats GenAI use statements as instructional design tools instead of compliance notices. Four use levels (Closed, Restricted, Conditional, and Open) place cognitive responsibility in different parts of the task. For example, a business instructor might allow GenAI to draft a crisis statement and then assess the learner's verification, critique, revision, and professional justification. C.O.D.E.S. may help instructors align GenAI expectations with learning outcomes, privacy safeguards, equitable alternatives, and defensible evidence of learner capability. The framework is conceptual and still needs empirical evaluation across disciplines, assessment types, institutions, and learner populations.

Copyright© The Author(s) 2025. Open Access under the Creative Commons Attribution 4.0 International License (CC BY 4.0). This license permits use, sharing, adaptation, distribution, and reproduction in any medium or format, giving proper credit to the original author, including a link to the license, and indicating if any changes were made. To view a copy of the licence, please visit https://creativecommons.org/licenses/by/4.0/

1. Introduction

Generative artificial intelligence (GenAI) complicates post-secondary assessment because it can produce text, code, images, and analyses that are hard to distinguish from learner-generated work. The central question is less whether GenAI was used than whether an assessment still gives defensible evidence of the intended learning outcome. Recent scholarship argues that assessment validity matters more than catching cheating, and that institutions need

structural changes to assessment, not surveillance alone (Dawson et al., 2024; Corbin, Dawson, & Liu, 2025).

Although institutional policies and syllabus statements establish shared baselines, such broad guidance rarely delineates which components of a specific task must remain learner-generated (Anselmo et al., 2024; Perkins et al., 2024; Xia et al., 2024). A course statement that says only "AI use is permitted with acknowledgement" is an example of a policy that fails in practice. It does not tell learners whether GenAI may interpret evidence, draft substantive content, or verify claims, so learners must interpret the rules themselves and decisions become inconsistent across assessments. Many instructors prefer simple, uniform rules because they are quick to write and apply, and that preference is reasonable given heavy workloads. Simplicity, however, leaves the instructional boundary undefined. Guidance at the assessment level is needed to connect GenAI permissions with learning outcomes, task stages, privacy boundaries, instructional supports, and accountability requirements.

This paper presents the C.O.D.E.S. framework, a practice-informed approach to designing and communicating assessment-level GenAI expectations for post-secondary instructors. C.O.D.E.S. asks instructors to Clarify the use level, offer supports, define permissions and prohibitions, explain relevance and rationale, and Set accountability and transparency expectations. The framework was developed from an educational developer's perspective in a Canadian polytechnic. Its contribution to the existing literature is a change in the role of the permission statement. A policy artifact tells learners what is allowed. An instructional tool links permitted use to intended evidence, learner support, privacy limits, rationale, and proportionate accountability for a given task. Existing scales and guidance describe levels of permitted use; C.O.D.E.S. adds a way to turn a chosen level into a complete, task-specific statement. A policy artifact operates retroactively, serving mostly as an instrument for institutional compliance and penalizing enforcement when boundaries are breached. In contrast, an instructional tool operates proactively. By integrating GenAI parameters directly into assessment design, the C.O.D.E.S. framework shifts the academic integrity conversation from catching unauthorized use to cultivating verifiable, transparent learning demonstrations. This shift from retroactive policing to proactive instructional scaffolding, represents the framework's core contribution to contemporary higher education literature.

2. Theoretical Foundations

By establishing intended learning outcomes and acceptable evidence first, backward design anchors the C.O.D.E.S. framework before any decisions are made regarding tasks or technologies (McTighe & Willis, 2019). Because GenAI can produce polished final products, instructors need to identify the knowledge, judgment, decisions, and performances that show achievement. Backward design does assume relatively stable outcomes and evidence, though, and GenAI capabilities change quickly. C.O.D.E.S. handles this tension by holding outcomes and acceptable evidence constant and treating tool permissions, safeguards, and documentation requirements as design decisions that can be revised as technologies evolve.

Adult learning principles establish the framework's foundation for relevance and informed agency (Knowles et al., 2020), whereas Transparency in Learning and Teaching

(TILT) operationalizes these core concepts by clarifying specific task purposes and success criteria (Tapp et al., 2019). Combined, both instructional approaches successfully eliminate hidden expectations, demonstrating exactly how defined GenAI boundaries protect learning rather than arbitrarily restricting it. Within C.O.D.E.S., backward design isolates critical evidence to protect; adult learning justifies why agency matters; and TILT renders the resulting academic expectations completely transparent for learners.

Universal Design for Learning (UDL) promotes the proactive removal of educational barriers alongside equitable alternatives (CAST, 2024). Within the C.O.D.E.S. framework, UDL explicitly distinguishes legitimate accessibility support from the problematic replacement of essential cognitive struggle. Concurrently, the SAMR model (Substitution, Augmentation, Modification, and Redefinition) operates strictly as a reflective lens for evaluating how GenAI changes specific academic tasks (Puentedura, 2013). C.O.D.E.S. firmly rejects viewing SAMR as a progressive ladder, avoiding the assumption that increased technological integration automatically results in deeper learning. Assessment validity is always the paramount governing principle as UDL confirms barrier mitigation while SAMR evaluates task transformation, functioning interdependently as design safeguards rather than isolated justifications for technology use.

Figure 1 shows how these foundations connect. Outcomes and acceptable evidence are the anchor, and the supporting theories then test transparency, relevance, access, and how much the task changes. The resulting C.O.D.E.S. statement communicates the decision and names the evidence needed to keep learner capability visible.

Figure 1: Integration of the theoretical foundations in C.O.D.E.S.

Design Anchor	Connected Design Checks	Assessment-level Output
Backward design: intended outcome and acceptable evidence	Adult Learning: relevance and agency TILT: purpose, task, and criteria UDL: barriers, supports, and equivalent alternatives SAMR: how GenAI changes the task	C.O.D.E.S. statement: level, supports, permissions, rationale, and accountability
Stable question: What capability must be demonstrated?	Dynamic question: What has changed about the tool, task, learner access, or risk?	Revisable statement aligned with policy, rubric, submission, and evidence

Source: Author-developed conceptual model.

3. Method and Materials

This conceptual design paper takes a design-based, practice-informed approach. The framework was developed by comparing three sources: contemporary scholarship on GenAI and assessment, established instructional theories used in faculty development, and recurring concerns observed in cross-disciplinary educational-development practice. The author works as an instructional facilitator and educational developer with instructors across programs, and that faculty-development position shaped the focus on decisions that can be explained, implemented, and reviewed with instructors.

The author developed the framework iteratively by grouping recurring practice problems into design functions, testing their capacity to distinguish cognitive responsibility, and revising the terminology for cross-disciplinary use. The practice patterns behind this work included broad course statements applied inconsistently to individual tasks, unclear boundaries between accessibility support and replacement of learning, uneven learner GenAI literacy, privacy concerns, and disclosure requirements that cost more than they added instructionally. The framework reflects one interpretation of practice in a Canadian polytechnic. No instructor or learner data were collected, so the method supports conceptual coherence and practical illustration but not claims of demonstrated effectiveness.

4. Procedural Decision-Making

Before drafting a GenAI use statement, instructors identify what learners must know or do independently. The question is not whether GenAI can perform the task but whether using it would replace the knowledge, judgment, or performance the assessment is meant to elicit. Prohibiting GenAI during a supervised medication calculation, for example, can be necessary when independent calculation is the evidence required for safe professional practice.

Once essential independent learning is established, educators must evaluate how the assessment fits within broader curricular sequencing. Foundational assessments may require independent performance because later learning builds on that capability. More advanced assessments may allow GenAI to handle routine drafting or generation once the intended outcome has moved toward evaluation, design, integration, or professional judgment. In a marketing task, for instance, a GenAI-generated crisis statement can become the object of critique when the outcome is to evaluate tone, bias, accuracy, and strategic appropriateness.

Finally, instructors weigh the non-equivalent priorities of policy, privacy, accreditation or licensure, accessibility, equity, learner autonomy, GenAI literacy, and workload. When they conflict, the chosen GenAI level should first preserve valid evidence of the learning outcome, and the other priorities then shape how that design is carried out through approved tools, clear boundaries, proportional documentation, aligned rubrics, and equitable alternatives. If a licensing body requires independent demonstration of a skill, for example, that requirement sets the level before other priorities are considered. Navigating these non-equivalent priorities often requires difficult instructional compromises. For example, while UDL might suggest offering a GenAI drafting assistant to reduce executive functioning barriers for some learners, strict professional licensure requirements may mandate unassisted, independent performance. IN instances where priorities clash, the C.O.D.E.S. framework establishes that the preservation of valid, licensable learning evidence must take precedence. However, the instructor remains responsible for actively mitigating the resulting accessibility barriers through non GenAI instructional supports. The process is iterative: if defensible boundaries, supports, or evidence requirements cannot be set, the task or use level should be reconsidered.

Decisions also vary by discipline (see Section 6). A supervised dosage calculation in health sciences may be Closed; brainstorming in the humanities may be Restricted while interpretation and argument remain learner generated; a GenAI crisis statement in business may be Conditional when critique and revision are assessed; and use in computer science may be Open when testing, security review, and modification of code are the intended professional

capabilities. No level is inherently safer, more rigorous, or more authentic than another. A defensible choice is the one that makes the intended capability observable under the relevant disciplinary and institutional conditions.

4.1 Decision Sequence

Figure 2 summarizes the decisions that instructors can follow for each assessment. If the learner's contribution is still unclear at the end, the instructor revises the task or chooses a more restrictive level.

Figure 2: Decision-making flowchart for selecting a GenAI use level

1. Identify Essential Capability	2. Test, Replace, or Reveal	3. Check Sequence and Discipline	4. Apply Constraints	5. Select Use Level	6. Align Evidence
What must learners know or do independently?	Would GenAI replace or reveal that capability?	Where does the task sit in the program, and what does the discipline expect?	What do policy, privacy, access, licensure, and workload require?	Closed, Restricted, Conditional, or Open?	Do supports, rubric, and accountability evidence match the level?
Feedback loop: if the learner's contribution would still be unclear, revise the task or choose a more restrictive level and repeat from Step 2.					

Source: Author-developed decision model.

5. The C.O.D.E.S. Framework

C.O.D.E.S. treats an assessment-level GenAI statement as a set of interconnected, instructional decisions. Clarify establishes the use level; Offer identifies the supports learners receive; Define specifies tools, functions, purposes, stages, and privacy boundaries; Explain links the decision to learning outcomes and professional or institutional expectations; and Set establishes the evidence learners must provide. As Figure 3 shows, the components are reciprocal, not strictly linear.

Figure 3: Relationships among the five C.O.D.E.S. components

Anchor: learning outcome and acceptable evidence of learner capability		
Clarify Sets the use level	**Define** Names tools, functions, stages, and data limits that make the level specific	**Explain** Justifies the level and the limits in terms of the outcome
Each decision is tested against the learner's ability to meet it and the instructor's ability to verify it		
Offer Exemplars, practice, peer learning, and equitable alternatives that let learners meet the boundary	**Set** Proportionate evidence that shows what the learner contributed	

Source: Author-developed conceptual model.

5.1 Clarify: GenAI Use Level

Closed use prohibits generative tools entirely, though embedded non-generative aids like spellcheck may remain acceptable. In this scenario, evidence relies strictly on direct, independent performance without any requirement for GenAI disclosure.

Moving beyond strict prohibition, Restricted use allows for limited preparatory support, such as brainstorming or drafting a generic outline. Despite this assistance, the learner must still generate the substantive reasoning, interpretation, and final product, while naming the tool and briefly explaining its contribution to a learner's preparation.

Whereas Restricted use limits GenAI to early-stage support, Conditional use shifts the instructional focus by permitting the technology to generate a defined part of the task itself. This approach requires learners to critically evaluate, revise, and justify that specific contribution. Consequently, assessment evidence centres on the learner's critique, judgment, and verification rather than the quality of the initial GenAI output.

Finally, Open use expands permission across the entire workflow. Although this broad access allows learners to utilize GenAI extensively, it does not lessen their academic responsibility; rather, it changes how that responsibility is demonstrated. In this highly collaborative mode, learners must direct the process, test and verify outputs, explain key decisions, and document contributions, ultimately taking full responsibility for the final product.

Table 1 summarizes how each level distributes cognitive responsibility, what it means for assessment validity, and the kinds of assessment each level suits.

Table 1: GenAI use levels, learner cognitive responsibility, and assessment validity considerations

Use Level	Permitted GenAI Use	Learner Cognitive Responsibility	Assessment Validity Considerations	Example Assessment Types
Closed	None; embedded non-generative tools such as spellcheck may remain acceptable	All substantive thinking and performance are independent	Evidence must come from direct, observable, independent performance	Supervised calculation, in-class exam, live skill demonstration
Restricted	Limited preparatory support, such as brainstorming or a generic outline	Learner interprets, reasons, decides, and produces the final work	Preparation must not displace the targeted reasoning; disclosure confirms the boundary	Primary-source analysis, argumentative essay, case analysis
Conditional	GenAI generates a defined part of the task for the learner to examine	Learner evaluates, verifies, revises, and justifies the GenAI contribution	Evidence is the quality of critique and revision, so the rubric must assess these, not the first output	Critique of a GenAI-drafted statement, annotated revision, fact-check of a GenAI summary

Use Level	Permitted GenAI Use	Learner Cognitive Responsibility	Assessment Validity Considerations	Example Assessment Types
Open	GenAI across the workflow, within approved tools and data limits	Learner directs the process, tests outputs, and owns the final product	Evidence is the learner's decisions, testing, and explanation of the human GenAI workflow	Software project with testing, design portfolio, capstone with decision log

Source: Author-developed framework.

5.2 Offer: Instructional Supports and Scaffolds

Once a use level is chosen, instructors identify the supports learners need to meet it. Useful supports include annotated exemplars, disclosure templates, checklists, aligned rubrics, practice activities, feedback, and citation guidance. Peer learning is also a support mechanism: guided comparison of sample prompts, collaborative critique of outputs, and discussion of why the same tool function suits one assessment but not another all show what acceptable GenAI use looks like. Supports should not assume that all learners arrive with the same literacy, and they should address accessibility without letting GenAI hide the capability being assessed (CAST, 2024; Moorhouse et al., 2023).

5.3 Define: Tools, Functions, Purposes, and Data Boundaries

Instructors specify approved tools and the permitted and prohibited functions, purposes, and stages of use. They also explicitly state what information remains restricted from tool inputs such as personal, clinical, or proprietary data; workplace confidentiality; and culturally sensitive or community owned knowledge. Decisions must follow current institutional policy, approved-tool guidance, accreditation or licensure requirements, and available institutional support. Learners should not have to create external accounts or disclose unnecessary information when a privacy-protective alternative can meet the same learning outcome.

Define must also account for the digital divide. Account creation, subscription cost, device quality, connectivity, and differing prior experience can all create unequal access to a named tool. An equivalent pathway, such as an institution-licensed tool, on-campus access, or a non-GenAI alternative, is needed whenever a barrier could decide who can meet the stated expectation. Institutional policy may also prohibit a tool or function that seems instructionally appropriate. C.O.D.E.S. supports clearer implementation of policy but does not override institutional, accreditation, licensure, or legal requirements.

5.4 Explain: Relevance and Rationale

A learner-facing rationale links GenAI boundaries to the learning outcome, assessment validity, institutional requirements, and professional expectations. Research on adult learning and autonomy support suggests that explicit relevance and meaningful boundaries can increase engagement and buy-in (Johansen et al., 2023; Knowles et al., 2020; Okada, 2023). The rationale tells learners that restrictions and permissions are instructional decisions made to preserve evidence of learning and are not arbitrary controls.

Learners experience this clarity differently from instructors. Before starting, a learner should be able to answer three questions: what am I allowed to do, why, and what must I show? When learners cannot answer those questions, they infer expectations from other courses or from peers, which is inequitable. A short check-in in which learners restate the boundary in their own words can reveal ambiguity before submission.

Instructors can formalize this learner perspective by embedding brief feedback loops, such as mid-semester surveys, anonymous exit tickets, or informal focus groups, directly into the course design. Actively capturing the learner's perspective on statement clarity allows instructors to identify where GenAI instructions may be misinterpreted. By treating learner feedback as vital implementation data, instructors can iteratively adjust their C.O.D.E.S. boundaries, ensuring the guidance remains an effective instructional scaffold rather than an unintended source of anxiety or confusion.

5.5 Set: Accountability and Transparency

Set requirements make the learner's contribution visible. Depending on the use level, evidence may include disclosure, citation, output verification, a structured critique, reflection, documented revisions, selected interaction records, test cases, or an explanation of key decisions. Requirements should be proportionate: instructors should collect only the evidence needed to preserve assessment validity and confirm that learners stayed within the stated boundaries. This treats integrity as a shared responsibility and encourages learners to evaluate GenAI contributions critically (Foltynek et al., 2023).

Disclosure formats should match the citation style learners are required to use. The following patterns use placeholders because GenAI citation conventions continue to change, and instructors should confirm them against the current style guide. APA: in-text citation (Developer, Year) with a reference entry in the form Developer. (Year). Tool name (Version) [Large language model]. URL. MLA: a works-cited entry that begins with a description of the prompt in quotation marks, followed by the tool name, version, developer, date, and URL. Chicago: a note in the form Text generated by Tool name, Developer, date, URL. Disclosure of how GenAI was used remains separate from citation of external sources.

6. Disciplinary Applications

Closed example (health sciences): During a supervised medication-calculation assessment, learners calculate dosages and show all work without GenAI. Practice problems, feedback, and non-GenAI accessibility supports are provided. Independent calculation is required because the assessment must establish safe performance.

Restricted example (humanities): Learners may use an approved tool to brainstorm themes or create a generic outline for a primary-source analysis. They independently interpret the sources, develop the argument, and write the analysis. The disclosure identifies the tool and explains how it shaped the initial structure.

Conditional example (business): Learners use GenAI to draft an initial crisis communication statement. They identify inaccuracies, bias, tone problems, and strategic weaknesses, submit a substantially revised version, and provide a structured critique. Evidence focuses on professional judgment and defensible revision.

Open example (computer science): Learners may use approved tools for ideation, code generation, debugging, documentation, and refinement. They test the final application, explain design decisions, document GenAI contributions, and assume responsibility for security, accuracy, and functionality.

Completed disclosure (Conditional, business): "I used Microsoft Copilot to draft an initial crisis statement. The draft contained an inaccurate timeline and a defensive tone. I corrected the timeline using the case documents, rewrote the opening to acknowledge responsibility, and removed unsupported claims. My annotated critique and revision rationale are attached."

Instructor rationale accompanying the statement: "This task assesses your professional judgment in crisis communication. Using GenAI for the first draft lets you practice evaluating and revising an imperfect statement, which is a routine part of the work. Your mark depends on the quality of your critique and revision, so please submit the original output, your annotations, and a brief explanation of your decisions."

7. Discussion and Implications

C.O.D.E.S. shifts attention from detecting unauthorized assistance to designing assessments that make learner capability visible. It adds an operational layer between institutional policy and individual tasks. Course-level guidance can establish consistency, while assessment-level statements specify where, why, and how GenAI may contribute without displacing essential cognitive responsibility.

For instructors, the framework offers a repeatable decision process, although implementation may at first increase redesign and evaluation work, particularly the effort of reviewing accountability evidence. Institutions can reduce that workload with reusable templates, common disclosure forms, discipline-specific examples, protected redesign time, and coordinated support from teaching and learning centres, privacy offices, libraries, accessibility services, academic integrity specialists, and program leaders. Large-enrolment courses need especially selective accountability requirements, because complete prompt histories create an unmanageable review burden and collect more learner data than the assessment needs. Scalable alternatives include a brief contribution statement, one annotated output, selected verification evidence, structured peer critique, or a short oral explanation for sampled or high-risk components.

Addressing the digital divide must also extend beyond individual assessment design into systemic institutional support. While the C.O.D.E.S. framework prompts instructors to offer equitable alternatives, the burden of ensuring technological equity cannot fall solely on faculty. Institutions must proactively manage the digital divide by securing campus-wide enterprise licenses for premium GenAI tools, providing offline alternatives, and maintaining accessible on-campus computing infrastructure. Without this systemic support, instructors risk designing Conditional or Open assessments that unintentionally penalize learners facing financial constraints, unreliable internet connectivity, or limited access to high-quality devices.

For learners, C.O.D.E.S. aims to clarify boundaries, supports, rationales, and responsibilities without assuming that wider GenAI access is more advanced or more equitable. For institutions, assessment-level statements put policy into practice by identifying approved

tools, privacy boundaries, alternatives, and required evidence. C.O.D.E.S. does not replace legal, privacy, accreditation, or institutional oversight.

7.1 Comparative Positioning

C.O.D.E.S. is meant to complement existing approaches, not replace them. The AI Assessment Scale offers levels of permitted AI involvement (Perkins et al., 2024) and STRIVE draws attention to emerging considerations in assessment design (Anselmo et al., 2024). Table 2 compares these approaches with syllabus-level statements. Institutional and syllabus-level statements can set a common baseline and may be enough when the same permission and evidence expectations truly apply to every task in a course. C.O.D.E.S. adds an assessment-level layer by connecting a selected level to supports, specific functions and stages, rationale, privacy boundaries, and evidence of learner contribution. Institutional policy can still limit implementation, because approved-tool availability, privacy requirements, and accreditation or licensure rules may narrow the levels available. C.O.D.E.S. cannot legitimize a use that policy prohibits.

Table 2: Comparison of syllabus-level statements, the AI Assessment Scale, and C.O.D.E.S.

Dimension	Syllabus-level Statement	AI Assessment Scale (Perkins et al., 2024)	C.O.D.E.S.
Primary Purpose	Sets a general course or institutional baseline	Describes graduated levels of permitted AI involvement	Guides design and communication of task-specific GenAI expectations
Assessment Validity	Addressed indirectly, if at all	Considered through the level chosen for each task	Anchored in the learning outcome and the evidence required
Learner Autonomy	Learners interpret broad rules on their own	Learners work within the stated level	Rationale and support enable informed choices within clear boundaries
Institutional Risk Management	Provides a consistent baseline for policy compliance	Offers a shared vocabulary across tasks	Adds task-level privacy limits, approved tools, and documented evidence within institutional policy
Best Suited To	Courses where the same rules apply to every task	Programs that want a common level language	Tasks where permitted use differ by stage, outcome, or discipline

Source: Author analysis based on Perkins et al. (2024).

7.2 Faculty Development, Scale, and Implementation

To ease the transition, instructors should follow several key implementation tips when using the framework for the first time. First, begin by applying C.O.D.E.S. to a single, consequential assessment rather than overhauling an entire course. Second, protect the essential

learning by letting the required independent evidence drive the choice of use level. Third, keep accountability proportional by requesting only the interaction evidence strictly necessary to preserve validity. Fourth, leverage approved institutional templates whenever possible to reduce initial drafting time. Finally, pilot the drafted C.O.D.E.S. statement with a colleague or learner representative to identify any unintended ambiguities before releasing the instructions to learners. Furthermore, establishing peer mentorship networks or communities of practice allows early adopters to share their successful C.O.D.E.S. statements, rubrics, and disclosure templates. When hesitant instructors can review localized, discipline specific examples developed by colleagues, the perceived risk of adopting a new assessment framework is reduced significantly.

7.3 Limitations

C.O.D.E.S. is a conceptual, practice-informed framework developed from one educational developer's interpretation of recurring concerns in a Canadian polytechnic setting. While designed for cross disciplinary application, the framework assumes a baseline of institutional readiness that may not exist in all learning environments. Its successful implementation relies heavily on institutions providing clear privacy guidelines, enterprise level tool licenses, and accessible alternatives for learners affected by the digital divide. In institutions lacking this centralized infrastructure, the administrative burden of ensuring equitable and safe GenAI use shifts entirely to the individual instructor, which could severely limit the framework's practical adoption. It has not been empirically validated, and no instructor or learner data were collected. The four levels may not capture every disciplinary practice, and level selection may vary across programs, jurisdictions, cultures, learner populations, and stages of study. The framework also depends on institutional clarity about approved tools, privacy, accessibility, academic integrity, and records management. Rapid changes in GenAI capabilities may require permissions and evidence requirements to be revised even when the learning outcome remains stable.

8. Recommendations for Future Study

Future investigation should ask: Do C.O.D.E.S. statements improve learners' interpretation of permitted use compared with general syllabus statements? Do the levels preserve valid evidence of learning across disciplines and assessment formats? What disclosure evidence is sufficient without creating excessive instructor workload or learner surveillance? How do access, disability, multilingualism, cultural context, privacy concerns, and prior GenAI experience affect clarity and participation across diverse learner populations?

Another equally critical line of study must address the practical realities of faculty workload and institutional scale. Transitioning from surveillance based academic integrity models to intentional, scaffolded GenAI assessment design requires significant instructor time investment. Future research should empirically measure this workload shift by asking if the time saved by reducing formal academic misconduct investigations offsets the initial hours required to draft C.O.D.E.S. statements, design aligned rubrics, and review interaction and verification evidence. Longitudinal studies could also evaluate the effectiveness of specific institutional interventions, like communities of practice, centralized template storage, and

protected redesign time to overcome initial instructor resistance and mitigate burnout during such a transition.

Furthermore, research should explore how instructional designers can leverage the C.O.D.E.S. framework beyond individual courses for program-level curriculum mapping. Instructional designers are uniquely positioned to audit course sequences and ensure GenAI competencies are scaffolded logically across a credential. Future empirical studies could examine how designers use the framework to protect foundational, independent learning through Closed assessments in introductory courses, before systematically introducing complex, Open level human GenAI collaboration in advanced courses.

9. Conclusion

C.O.D.E.S. treats GenAI use statements as part of assessment design rather than simple compliance checkboxes. By connecting permissions, learner supports, tool boundaries, rationale, and accountability to the learning outcome, the framework offers a practical methodology to turn broad institutional expectations into task-specific guidance. The Closed, Restricted, Conditional, and Open levels distribute cognitive responsibility differently; importantly, they are not a hierarchical ranking of educational value or academic rigour.

To move beyond reactive surveillance, institutions must urgently connect policy, instructor decision-making, and learner-facing guidance instead of treating them as disconnected administrative layers. When these elements remain misaligned, academic integrity efforts often devolve into adversarial policing. True alignment occurs when policy defines the legally permissible and technically supported space, instructors confidently translate that space into outcome aligned assessment decisions, and learners receive the clear explanations, supports, alternatives, and accountability expectations necessary to act ethically and responsibly. Institutions must demonstrate leadership by funding targeted faculty development, securing equitable access to approved tools, providing centralized disclosure templates, and protecting instructor time for assessment redesign.

GenAI capabilities will continue to evolve at an unprecedented pace. The alignment fostered by the C.O.D.E.S. framework is designed to outlast any fixed tool list. While specific models will inevitably become obsolete, the underlying andragogical imperative of protecting the learning outcome and demanding defensible evidence of human cognition will remain the stable anchor of higher education. The framework is informed by established instructional theory and oriented toward practical application, establishing a clear imperative for future empirical testing to validate its proposed educational benefits.

10.Artificial Intelligence Tools Disclosure

Microsoft Copilot was used for language refinement, structural feedback, and manuscript condensation. All conceptual framing, analysis, source selection, verification, and conclusions remain the author’s original intellectual work.

References

Anselmo, L., Eaton, S. E., Jivani, R., Moya, B., & Wright, A. (2024). STRIVE: Emerging considerations when designing assessments for artificial intelligence use. University of Calgary, Taylor Institute. https://doi.org/10.11575/PRISM/46820

CAST. (2024). Universal design for learning guidelines, version 3.0. https://udlguidelines.cast.org/

Corbin, T., Dawson, P., & Liu, D. (2025). Talk is cheap: Why structural assessment changes are needed for a time of GenAI. Assessment & Evaluation in Higher Education, 50(7), 1087–1097. https://doi.org/10.1080/02602938.2025.2503964

Dawson, P., Bearman, M., Dollinger, M., & Boud, D. (2024). Validity matters more than cheating. Assessment & Evaluation in Higher Education, 49(7), 1005–1016. https://doi.org/10.1080/02602938.2024.2386662

Foltynek, T., Bjelobaba, S., Glendinning, I., Khan, Z. R., Santos, R., Pavletic, P., & Kravjar, J. (2023). ENAI recommendations on the ethical use of artificial intelligence in education. International Journal for Educational Integrity, 19, Article 12. https://doi.org/10.1007/s40979-023-00133-4

Johansen, M. O., Eliassen, S., & Leno, L. M. (2023). The bright and dark side of autonomy: How autonomy support and thwarting relate to student motivation and academic functioning. Frontiers in Education, 8, Article 1153647. https://doi.org/10.3389/feduc.2023.1153647

Knowles, M. S., Holton, E. F., Swanson, R. A., & Robinson, P. A. (2020). The adult learner: The definitive classic in adult education and human resource development (9th ed.). Routledge.

McTighe, J., & Willis, J. (2019). Upgrade your teaching: Understanding by design meets neuroscience. ASCD.

Moorhouse, B. L., Yeo, M. A., & Wan, Y. (2023). Generative AI tools and assessment: Guidelines of the world's top-ranking universities. Computers and Education Open, 5, Article 100151. https://doi.org/10.1016/j.caeo.2023.100151

Okada, R. (2023). Effects of perceived autonomy support on academic achievement and motivation among higher education students: A meta-analysis. Japanese Psychological Research, 65(3), 230–242. https://doi.org/10.1111/jpr.12380

Perkins, M., Furze, L., Roe, J., & MacVaugh, J. (2024). The AI assessment scale (AIAS). Journal of University Teaching and Learning Practice, 21(6), 1–18. https://doi.org/10.53761/q3azde36

Puentedura, R. R. (2013). SAMR model. http://www.hippasus.com

Tapp, S., Boye, A., & Winkelmes, M.-A. (Eds.). (2019). Transparent design in higher education teaching and leadership. Stylus.

Xia, Q., Weng, X., Ouyang, F., Lin, T. J., & Chiu, T. K. F. (2024). A scoping review of generative AI and assessment. International Journal of Educational Technology in Higher Education, 21, Article 40. https://doi.org/10.1186/s41239-024-00468-z

How to cite this article:
Manweiler J. (2026) 'Empowering Educators: Using the C.O.D.E.S. Framework to Design Generative AI Use Statements in Higher Education, *International Multidisciplinary Research Journal*, Volume V; November 2026; Page 39-52. DOI: https://doi.org/10.47722/imrj.2001.90

Appendix A: C.O.D.E.S. Practitioner Quick-Start and Template

Use this sequence after identifying the assessment learning outcome and acceptable evidence.

1. Identify essential capability: What must learners know, decide, create, calculate, perform, or justify?
2. Select the level: Closed for independent performance; Restricted for limited preparation; Conditional for critique or revision of a defined GenAI contribution; Open when directing and defending a human GenAI workflow is relevant.
3. Complete C.O.D.E.S.: Clarify the level; Offer supports and an equivalent alternative; Define tools, functions, stages, purposes, and data limits; Explain the rationale; Set proportionate evidence requirements.
4. Check alignment: Ensure that the instructions, rubric, submission requirements, privacy guidance, and academic-integrity expectations protect the same learning outcome.

Adaptable Learner-facing Template

GenAI use level: [Closed, Restricted, Conditional, or Open]. For this assessment, you may [permitted tools, functions, purposes, and stages]. You may not [prohibited tools, functions, purposes, or stages]. These boundaries are in place because the assessment is designed to demonstrate [outcome or essential capability]. To support completion, you may use [exemplars, practice, feedback, templates, peer learning, citation guidance, accessibility supports, or other resources]. If the named tool creates an access, privacy, accessibility, or cost barrier, [equivalent pathway]. Do not enter [restricted data]. Submit [proportionate disclosure, output, critique, verification, revision explanation, reflection, test results, or decision rationale]. You remain responsible for accuracy, acknowledgement, and the final submission.

Appendix B: Key Terms

Accountability evidence: The disclosure, critique, verification, reflection, or other record that shows what a learner contributed.

Assessment validity: The extent to which an assessment gives sound evidence of the intended learning outcome.

Backward design: A planning approach that starts with intended learning outcomes and acceptable evidence before selecting tasks.

Cognitive responsibility: The thinking, judgment, and decisions that the learner, and not the tool, must carry out.

Use levels (Closed, Restricted, Conditional, Open): The four assessment-level categories of permitted GenAI use described in Table 1.

SAMR: Substitution, Augmentation, Modification, and Redefinition, a model for reflecting on how technology changes a task (Puentedura, 2013).

TILT: Transparency in Learning and Teaching, an approach that states the purpose, task, and criteria of an activity (Tapp et al., 2019).

UDL: Universal Design for Learning, a framework for removing barriers and providing flexible options (CAST, 2024).