Moving Towards a Novel Framework for Academic Integrity and Assessment in the Age of Generative Ai

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ABSTRACT

Generative AI has moved from a novel idea to standard academic practice, with recent surveys indicating high student adoption in some higher-education samples, including 95% reporting academic use in one multi-level survey(Gámez-Guadix & Mateos-Pérez, 2026). Now, the differentiator for institutions is no longer whether students use AI, but whether they are taught to use it well, that is, whether they are using it with critical thinking, verification habits, and professional judgment. Unfortunately, institutional policy has not updated with this shift. Most higher education institutions still lack formal AI-use policies (Song, 2024) , which leaves individual instructors to set ad-hoc rules (Mack & Byanjankar, 2025a) , and academic misconduct linked to generative AI is rising sharply (Song, 2024) , with plagiarism-detection systems poorly equipped to identify AI-assisted work and many institutions lacking such facilities (Phornprasert et al., 2026a; Wang et al., 2024)

This paper asserts that the current institutional response, like restrictions and detection, misdiagnoses the problem. The central question is no longer whether students are using AI, but whether that use is building student agency or fostering dependency, and assessment design has a decisive role in determining which outcome prevails. Drawing on recent policy literature and institutional case studies, this paper repositions AI literacy as a form of academic integrity rather than its opposite. It treats disclosed, critically evaluated AI use as a demonstrable skill, and undisclosed or uncritical use as the actual integrity violation. The framework proposes three assessment design principles: process-visible tasks, tiered disclosure requirements, and embedded AI-literacy instruction within disciplinary curricula. It is concluded that institutions treating AI purely as a threat will fall further behind those that treat it as a literacy to be taught, with implications for curriculum design, curriculum articulation, and evaluation, which raises many cardinal issues for teacher education.

Key Terms: Generative AI, academic integrity, assessment design, AI literacy, higher education policy**.**

INTRODUCTION

Generative AI has become a standard academic practice, with recent surveys indicating a high student adoption rate in some higher-education samples, including 95% reporting academic use in one multi-level (Gámez-Guadix & Mateos-Pérez, 2026) and 96.8% reporting use of ChatGPT in another cross-linguistic survey (Gusman et al., 2026). The emergence of generative artificial intelligence in education offers both opportunities and challenges, particularly in the case of student assessment(Khlaif et al., 2024) . This shift has outpaced institutional response that a substantial proportion of higher education institutions still lack formal, consistent AI-use policies, leaving individual instructors to set ad-hoc rules on a course-by-course basis(Perkins et al., 2024; Zlotnikova et al., 2026). Meanwhile, the conventional detection tools remain unreliable and are increasingly avoided through paraphrasing, lightly editing, and deliberately humanizing(Perkins et al., 2024) . The result is a widening gap between how students actually work and how institutions attempt to govern that work(Phornprasert et al., 2026b)

Most of the institutional response to generative AI in assessment has been restriction and detection such as banning tools, deploying detection software, or treating any AI involvement as inherently suspect(Mack & Byanjankar, 2025; Perkins et al., 2024) . This paper argues that this response misdiagnoses the underlying problem. Disclosure-based alternatives, such as graduated "traffic-light" policies, have gained traction as a moderate approach, but it produces the risk of enforcement illusion, that is an appearance of oversight without a genuine verifiable mechanism to verify that declared use matches actual practice(Fasterling, 2012; Fung et al., 2007). So, today's relevant question is no longer whether students are using AI, but whether that use is building student agency and critical judgment or fostering passive dependency. Current approaches are poorly designed to distinguish between the two(Furze et al., 2024; Ucan, 2026) . So, apart from policy prohibition, Assessment design is what ultimately determines which outcome prevails, yet assessment redesign remains underexplored compared to the volume of literature on detection and policy(Furze et al., 2024; Khlaif et al., 2024) .

Objectives of the Study

Guided by this problem, the study is structured around the following objectives:

1. To propose a conceptual framework of assessment design principles, namely, process-visible tasks, tiered disclosure requirements, and embedded AI-literacy instruction which is theoretically grounded in constructive alignment (Biggs, 1996; Patrick Stokkink, 2025)

2. To draw out implications of this framework for curriculum design, evaluation practice, and teacher education.

Scope and Approach

This is a conceptual, qualitative paper, developed through synthesis of existing peer-reviewed literature, institutional case studies, and current policy discourse rather than through primary data collection. The aim of this paper is to develop and justify a theoretical framework and not to empirically test it. Empirical validation of the proposed principles is identified as a direction for future research.

METHODOLOGY / CONCEPTUAL APPROACH

This study adopts a conceptual, qualitative approach consistent with its aim of developing and justifying a theoretical framework for assessment redesign rather than testing an intervention through primary data collection or conducting a statistical meta-analysis. Conceptual scholarship is appropriate here because it integrates dispersed empirical findings, policy guidance, and theoretical arguments into a coherent model that can later be operationalized and tested. This choice is especially warranted in the GenAI assessment literature, where recent reviews describe a rapidly evolving field marked by fragmented evidence, emerging design patterns, and uneven institutional readiness(Crompton & Burke, 2026; Yasfi, 2026) .

To ensure transparency, the literature base was gathered through a structured search conducted within the Scopus and Google Scholar database. The search strategy employed combinations of core such as 'AI Assessment', 'Artificial Intelligence Ethics', 'Academic Integrity', and 'Generative AI'. After screening titles, abstracts, and thematic relevance focusing on assessment redesign models and institutional governance, a targeted corpus of peer-reviewed scholarship, preprint studies, and policy documents was selected.

This evidentiary base was selected because current work on GenAI and assessment spans systematic reviews of assessment redesign(Yasfi, 2026) , conceptual models of integrity as a systemic design problem (Chase & Galvin, 2026; Maleki, 2026), and policy analyses showing convergence around disclosure, process evidence, and verification practices despite persistent governance gaps(Başoğlu, 2026; Singh et al., 2026)

Instead of performing a quantitative effect-size meta-analysis, this study utilizes conceptual synthesis, which is organized through constructive alignment (Biggs, 1996) which holds that learning outcomes, teaching activities, and assessment must be deliberately aligned. Different insights regarding curriculum design, task

structure, and verification policies were synthesized to construct the three-part framework proposed in this paper linking curriculum, task design, and verification policy.

Repositioning AI Literacy within Academic Integrity

From Restriction to Literacy: A Conceptual Shift

The current institutional responses to generative AI are banning tools, deploying detection software and treating any AI involvement as inherently suspect rests on an assumption that AI use itself is the integrity problem(Ali & Maroulis, 2026). This paper claims that assumption is mistaken and that the institutions are directed toward the wrong target. The detection-based approaches remain poorly equipped to identify AI-assisted work and disclosure-based alternatives such as traffic-light or declarative systems risk producing an enforcement illusion, that is an appearance of oversight without a genuine mechanism to confirm compliance (Corbin et al., 2025) Both approaches share a common mistake that they treat the presence of AI as the object of concern, rather than the quality of a student's engagement with it. A definition of integrity built only around restriction cannot distinguish a student who used AI to validate an argument they had already built from one who submitted AI output without meaningfully engaging with it at all, because it never asks that question in the first place(Dushenkov et al., 2026).

Disclosed, Critical AI Use as a Demonstrable Skill

This paper argues disclosed and critically evaluated AI use as evidence of a skill worth assessing, not a violation to be policed. This follows from constructive alignment theory(Biggs, 1996) recently extended to generative AI contexts (Patrick Stokkink, 2025)which holds that intended learning outcomes, teaching activities, and assessment must be knowingly aligned. If an institution's learning outcomes now include the capacity to use AI critically and responsibly, which is an increasingly explicit expectation in higher education broadly and within India's National Education Policy 2020 specifically, then demonstrating that capacity should be treated as a skill, not a violation against it(Dushenkov et al., 2026; Yaacob et al., 2026). This reframing is consistent with recent calls to treat integrity as something enacted through visible evaluative judgement rather than something verified looking back through detection.

Correspondingly, this paper locates the actual integrity violation not in AI use itself, but in its disguise or its uncritical, unexamined adoption. This is consistent with existing academic integrity practice, where admission of unacknowledged generative AI use is already treated as a direct indicator of misconduct, alongside other established red flags such as a student's inability to answer questions about their own submitted work (Guy Curtis, 2026).Undisclosed use denies an assessor the ability to evaluate a student's actual contribution. Uncritical use, meanwhile, is a pedagogical failure as much as an integrity one. A student who submits AI output without evaluating, verifying, or revising it has not demonstrated the relevant learning outcome, independent of whether they disclosed it. This is precisely why disclosure alone is an insufficient safeguard(Dushenkov et al., 2026; Hershkovitz et al., 2025). So, evidence of the *quality* of engagement, which process-visible tasks and, for higher-stakes assessment, oral verification are specifically designed to surface.

Implications for How Integrity Is Assessed

Repositioned this way, academic integrity in the generative AI era is not to check whether AI is used or not used in a submission, but a quality of engagement that must be actively assessed, in the same way originality or argument quality already are. This reframing is what makes the three-principles framework in the following Section necessary. If integrity is a quality of engagement rather than a fact of tool use, evaluating it requires assessment design capable of surfacing that engagement, which restriction and detection-based approaches are not able to do.

Most of the existing institutional responses predominantly rely on binary restriction policies or unverified 'traffic-light' disclosure systems, which risk creating an enforcement illusion without verifying actual practice. The proposed framework introduces a more resilient approach. Unlike conventional models that treat AI presence as a violation or rely solely on unsupported declarations, our three-part model bridges tiered

disclosures with process-visible evidence and discipline-embedded AI literacy, shifting the focus from policing tool use to evaluating critical student engagement.

The Proposed Framework: Three Assessment Design Principles

This paper proposes a three-part framework for redesigning assessment in the age of generative AI namely process-visible tasks, tiered disclosure requirements, and embedded AI-literacy instruction. The framework lures on constructive alignment theory (Biggs, 1996), which says that intended learning outcomes, teaching activities, and assessment must be deliberately aligned rather than treated as separate interventions. This approach is recently extended specifically to generative AI contexts (Stokkink, 2025). The curriculum defines what students should be able to do with AI, task design assesses whether they are able to do it, and disclosure requirements verify that the two remain aligned. The three principles are not independent principles but function as a single, interrelated intervention, developed through analysis of current literature on assessment design, institutional policy, and AI-literacy pedagogy

Process-Visible Tasks

Process-visible tasks are assessment designs that make a student's reasoning traceable and shifts evaluation from final-product quality toward demonstrable decision making and ownership of learning. This brings a shift proposed in recent literature toward process-oriented evaluation. The assessment is built around research logs, documented decisions about how AI-suggested material was evaluated, and reflections on what was revised and why, rather than lying on a single polished final submission. The foundation is theoretical as much as practical: generative AI produces fine outputs without capturing the nature of human thinking. And the ability to reflect on one's own reasoning is itself a sincere feature of assessment. So, in this way, academic integrity becomes something enacted and made visible through the task itself, rather than something verified after the fact through detection software.

Tiered Disclosure Requirements

Tiered disclosure requirements mean the amount of detail a student must give about AI use should depend on how much the AI contributed to the assignment, rather than using the same rule for every assessment. In practice, this resembles the systems that are already implemented at several institutions, where AI use is categorized as prohibited, conditionally permitted, or fully permitted depending on the assignment. However, disclosure requirements alone have a documented weakness: without a mechanism to verify what is disclosed, they risk creating an "enforcement illusion" which give institutions a sense of oversight without any real means of confirming that a student's declared AI use matches their actual process. This paper argues that tiered disclosure only becomes a meaningful safeguard when anchored to process-visible tasks, because a disclosure claim can then be checked against the visible reasoning path the task itself produces.

Embedded AI-Literacy Instruction within Disciplinary Curricula

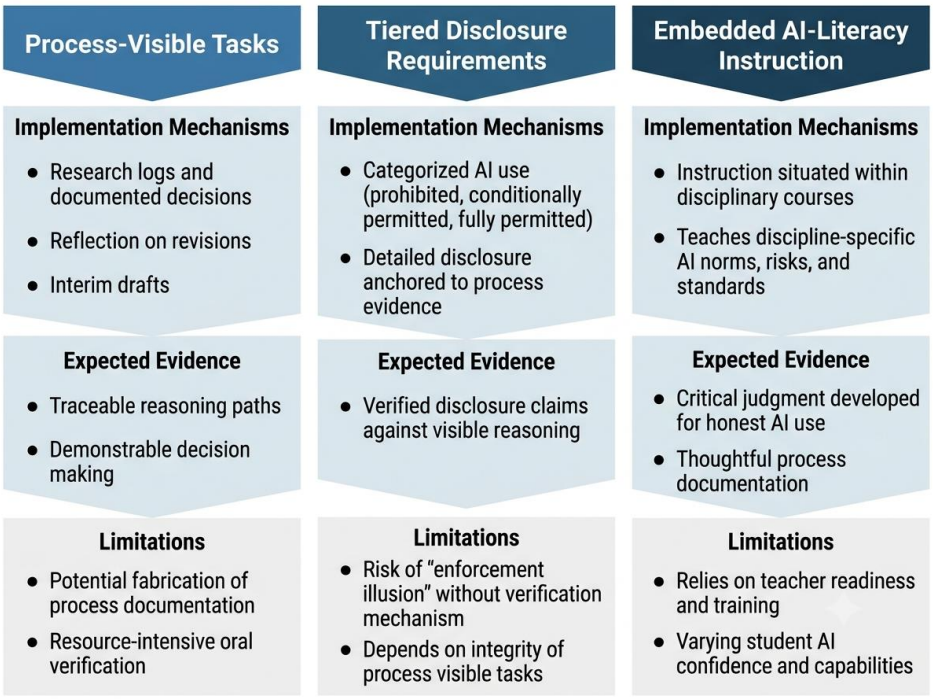
The third principle addresses a precondition underlying the first two, that is, students cannot meaningfully engage in process-visible tasks or make honest disclosures about AI use without first developing the critical judgment to use AI. Embedded AI-literacy instruction situates this learning within disciplinary courses themselves, apart from delivering it as a standalone, generic module(Farooqui et al., 2024). This reflects both institutional practice that several universities have begun implementing discipline-integrated AI literacy initiatives and direct evidence from students themselves, who report low confidence in their current AI skills and have explicitly called for discipline-specific instruction(Cheng et al., 2026; Morell-Mengual et al., 2025). Embedding AI literacy within the discipline ensures that students learn not just how to use AI tools, but how the norms, risks, and standards of evaluation differ within their specific field of study.

Interrelationship of the Three Principles

Together, the three principles form a single coherent design logic. Process-visible tasks generate the evidence needed for disclosure to be meaningful and disclosure which is anchored to that evidence becomes a verifiable

requirement other than just a declaration. Then the embedded AI-literacy instruction supplies the underlying capability that makes both honest disclosure and thoughtful process documentation possible in the first place. In this framework, Academic integrity is not achieved by restricting or detecting AI use, but by designing assessment, policy, and curriculum to work together toward the same end.

Figure 1. Structural Framework of the Three Assessment Design Principles



Implications

The proposed framework carries implications across three interconnected areas of practice.

- **Curriculum design:** AI literacy should be embedded within disciplinary learning outcomes rather than delivered as a standalone module, requiring each field to articulate what critical AI use looks like within its own knowledge practices that is consistent with student demand for discipline-specific instruction (Obura & Emoit, 2024; Perdana et al., 2026; Yaacob et al., 2026) and with constructive alignment's requirement that outcomes, teaching, and assessment remain aligned (Biggs, 1996).

- **Assessment practice:** Task design should generate process evidence by default, that are drafts, logs, and reflective components built in from the outset with grading rubrics made explicit about distinguishing disclosed, critical AI use from undisclosed or uncritical use. This raises real resource and scalability questions, particularly for oral verification checkpoints, which this paper identifies as a matter for institutional judgment.
- **Teacher education:** Pre-service and in-service training should explicitly prepare teachers to design AI-resilient assessment rather than merely detect AI misuse, particularly relevant within the digital-integration goals of NEP 2020 and recent calls for holistic AI-literacy curricula in teacher education. Without this preparation, individual teachers are left to develop ad hoc classroom responses, reproducing at the classroom level the same policy fragmentation identified at the institutional level.

Operationalizing this framework should be careful because of practical constraints, including cross-disciplinary adaptability, equity, privacy, and faculty workload. First, what counts as "critical engagement" varies widely by subject such as argument verification in the humanities versus code optimization in technical disciplines. Second, institutions must provide equal access to necessary AI tools and allow flexible, multimodal submission formats so digitally marginalized students are not disadvantaged to ensure equity and accessibility. Data privacy is another major concern asking students to show their working process should rely on their own reflective notes rather than intrusive surveillance or monitoring software. Finally, to prevent

increases in staff workload, verification mechanisms like oral defence should be reserved for high-stakes summative evaluations, while lightweight reflective prompts are suggested for routine formative tasks.

LIMITATIONS

This framework does not claim to eliminate the possibility that a student misrepresents their AI use. Process documentation could in principle be fabricated using AI-generated revision histories and oral defence could in principle be prepared for or coached. No assessment design, including detection software, restriction policies, or disclosure statements used in current practice is immune to determined evasion. What this framework offers instead is resilience. Each additional layer (visible process, evidence-anchored disclosure, oral verification) raises the effort required to sustain a false account and increases the likelihood that inconsistencies become detectable, compared to current approaches that rely on a single, unverifiable disclosure statement or on detection tools with known accuracy limitations. Consistent with recent framework proposals in this space, this paper positions its contribution as AI-resilient rather than AI-proof, and identifies empirical testing of the framework's actual resistance to misrepresentation as a necessary direction for future research beyond the scope of this conceptual paper.

CONCLUSION

This paper set out to address a specific and important problem, which is institutional responses to generative AI in assessment have overwhelmingly relied on restriction and detection policies only. These approaches misdiagnose the underlying challenge and remain increasingly unreliable as detection tools are circumvented and AI use becomes near-universal among students. In response, this paper proposed a three-principle framework that are process-visible tasks, tiered disclosure requirements anchored to verifiable evidence, and embedded AI-literacy instruction within disciplinary curricula — theoretically grounded in constructive alignment (Biggs, 1996; Patrick Stokkink, 2025) and developed through synthesis of current literature on assessment design, institutional policy, and AI-literacy pedagogy.

The central argument is that academic integrity in the generative AI era should be understood not as the absence of AI use, but as the presence of disclosed, critical engagement with it. The paper is repositioning AI literacy as a demonstrable skill rather than treating all AI involvement as inherently suspect. The proposed framework operationalizes this repositioning by ensuring that curriculum builds the judgment required for honest engagement, task design generates the evidence needed to verify it, and disclosure is anchored to that evidence rather than standing alone as an unverifiable claim.

This study has been explicit throughout about what the framework does not claim. It does not offer a lie-proof or AI-proof solution. The process documentation and oral verification can, in principle, still be circumvented by a sufficiently motivated student. What the framework offers instead is resilience by raising the effort, consistency, and detectability demanded of any attempt at twisting, compared to current approaches that rely on a single, unverifiable disclosure statement or on detection software of limited reliability. Also, this paper does not claim empirical validation. As a conceptual, qualitative contribution, its purpose is to develop and justify a theoretical structure, not to test it. Empirical evaluation of the framework's actual effectiveness, including how students respond to process-visible tasks in practice, and whether oral verification checkpoints meaningfully improve detection of misrepresentation remains a scope for future research.

The implications developed point toward a broader reframing. The institutions that treat generative AI purely as a threat to be policed will likely continue to fall behind those that treat it as a literacy to be taught. This has particular relevance within the Indian higher education context, where NEP 2020's emphasis on digital integration and pedagogical reform creates both the mandate and the opportunity to embed AI-resilient assessment design into teacher education and curriculum policy from the outset, rather than retrofitting it in response to institutional crisis. In this sense, the framework proposed here is offered not as a finished solution, but as a starting structure. The one intended to be tested, adapted, and refined as generative AI, and the institutional response to it, continues to evolve.

Declaration of AI Use

During the preparation of this work, the authors used AI tools for grammar correction and improving language and readability.

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