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Proceedings of the World Conference on Teaching and Education
Vol. 4, Issue. 2, 2025, pp. 42-58
DOI: https://doi.org/10.33422/worldcte.v4i2.1756
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ISSN: 2783-7793 online

Beyond Task Delegation: Reconceptualising Instructional Design to Measure Competence in the Age of Generative AI

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Abstract

The rapid proliferation of Large Language Models (LLMs) has invalidated traditional content-recall assessments, acting as a catalyst for a systemic transition towards Competence-Based Education (CBE). This paper contends that the role of faculty must transcend content dissemination, focusing instead on observable human competencies associated with Metacognition and Self-Regulated Learning (SRL). Drawing upon Behaviourism and Bloom's Taxonomy, we propose the Reverse-Flipped Model. This conceptual framework, supported by illustrative disciplinary cases in History, Computer Science, Digital Photography, and Composition, utilises generative tools for low-stakes production to repurpose pedagogical time for high-stakes human intervention. Prompt Literacy is conceptualised as an observable instructional competency that externalises planning, monitoring, evaluation, and strategic intervention behaviours during human-AI collaboration. Implementation necessitates the use of Analytic Rubrics and Automated Process Portfolios (APP) to document observable demonstrations of Prompt Literacy and strategic engagement over final product quality. The framework addresses institutional sustainability and the moral imperative of digital equity. The primary contribution of this framework is a structural shift that enhances assessment validity by ensuring student success is defined by verifiable mastery of human-led strategic intervention rather than machine-generated output.

Keywords: Generative AI, Competence-Based Education (CBE), Self-Regulated Learning (SRL), Metacognition, Reverse-Flipped Model, Assessment Validity, Prompt Literacy

1. Introduction

The emergence of Large Language Models (LLMs) has fundamentally restructured the information environment, fostering a pervasive educational ecosystem characterised by ubiquitous access to immediate content synthesis and task execution. This rapid adoption precipitates a collapse of the "content monopoly" historically maintained by academic institutions. When LLMs can flawlessly execute tasks contingent upon content recall,

traditional assessment modalities are rendered obsolete (Jensen et al., 2024). Consequently, the long-standing assumption that a final product serves as a reliable proxy for evidence of learning is effectively "dead" (Janio, 2025b). This transformation is not merely an isolated disruption but a global phenomenon reshaping academic practices through a complex balance of efficiency gains and ethical imperatives (Mohammadi et al., 2026). This paradigm shift has catalysed a critical "delegation crisis." When artificial intelligence can autonomously perform low-stakes, content-dependent academic labour, the validity of assessments designed to measure human competence is fundamentally compromised (Dawson et al., 2024; Luo, 2024). In this new reality, the priority must shift: Dawson et al. (2024) correctly posit that "validity matters more than cheating" (p. 5), necessitating a pivot towards certifications that verify a student's capacity to function within an AI-pervasive professional landscape. The pedagogical challenge has thus evolved beyond the detection of academic dishonesty; it now requires a structural recognition that assignments failing to distinguish between genuine skill and machine output are inherently invalid. As Janio (2025b) suggests, tasks completed by AI in seconds likely measure a mere "proxy for learning" rather than the "deep work of human thought" (para. 4).

Historically, higher education has relied upon a content-coverage framework, utilising seat time and standardised test scores as primary metrics (Farmer, 2024). This approach is now fundamentally fractured. The ability of Generative AI (GenAI) to automate passive instructional components with maximum efficiency (AlAfnan et al., 2023) exposes a growing discrepancy between passive exposure and verifiable competence. Vieriu and Petrea (2025) describe this transition as "double-edged," offering the potential to either "liberate students" for higher-level cognition or "trap them" in passive dependency (p. 343). However, the disruption of traditional proxies also invites the development of adaptive systems that tailor educational content to individual progress, potentially bridging the gap between standardised curricula and personalised competency development (Gligorea et al., 2023).

Ultimately, the core challenge facing the academy is structural: the inherent invalidity of legacy instructional design when confronted with tools capable of high-level delegation (Dawson et al., 2024; Luo, 2024). Because the boundary between integrity and assistance has become "'absurdly' thin" (Luo, 2024, p. 6188), institutions must transition from policing tools to quantifying a student's "unique critical intervention." This obsolescence necessitates a systemic shift towards genuine competency measurement, compelling educators to fundamentally reconceptualise the very nature of academic labour (Janio, 2025a).

In response to these challenges, this paper proposes a process-based approach to competence-based assessment in AI-integrated learning environments. It argues that instructional and assessment practices must prioritise observable human competencies over machine-generated outputs. The Reverse Flipped Model is introduced as an instructional design framework that reallocates low-stakes AI-assisted production to create opportunities for high-stakes human intervention. Prompt Literacy is conceptualised as an observable instructional competency that reflects students' strategic engagement with generative AI tools. The study further introduces process-based assessment artefacts that document planning, monitoring, evaluation, and strategic intervention behaviours associated with self-regulated learning. Together, these contributions foreground human judgement and critical intervention in the age of Generative AI.

2. Literature Review and Theoretical Framework

AI as Enforcer of Competence

The theoretical foundation for this instructional shift is rooted in Behaviourism, specifically B.F. Skinner's (1974) principle that learning represents an "observable and measurable change" in behaviour shaped by environmental stimuli (p. 18). In the contemporary landscape, the learning environment universally includes Generative AI, establishing a novel set of contingencies. Consequently, instructional design can no longer passively tolerate machine output; it must be behaviourally designed to reinforce desirable student actions—such as critical evaluation and synthesis—while explicitly deterring "passive delegation" or surface-level reliance on AI (Vieriu & Petrea, 2025). Vieriu and Petrea (2025) note that this forces an institutional shift from "rote memorization" toward evaluative skills (p. 345), effectively repositioning AI as a tool that "bottom-fills" lower-order cognitive tasks. To address the resulting demand for higher-order thinking, the most significant challenge in assessing AI-proof cognitive skills must be overcome: their intrinsically internal nature. As Bloom (1956) argues, higher-order cognitive achievement necessitates the "organization and reorganization of experience" into new patterns (p. 38). Therefore, the core innovation of this framework is to leverage behaviourist principles to ensure the cognitive process of metacognition is externalized and made observable through structured process documentation. By requiring students to demonstrate "measurable actions" through prompt logs and intervention narratives (Skinner, 1974, p. 18), faculty can design tasks that specifically target high-level skills, making assessment immune to delegation. This shift reframes the educational goal from sufficient content delivery to verifiable "behaviour change" or competency attainment, confirming the institutional inevitability of Competency-Based Education (CBE) (Farmer, 2024). As Farmer (2024) suggests, CBE repurposes the AI tool as a "plowshare for cultivation" rather than a disruptive force (para. 8).

Metacognition and Self-Regulated Learning (SRL): Observable Competencies for AI-Assisted Learning

Effective human-AI partnership requires advanced internal processes that govern strategic behavior, namely Metacognition and Self-Regulated Learning (SRL). Zimmerman (2008) defines self-regulation as the "self-directive process" by which learners transform mental abilities into academic skills (p. 166), a process wherein metacognition serves as the primary "monitor and controller" (Lajoie, 2008, p. 470). SRL encompasses a cyclical flow of planning, monitoring, evaluation, and intervention (Tezer, 2025). Winne (2017) posits that learners must utilize specific "cognitive tactics" to monitor their progress (p. 42), making these skills particularly important for strategic engagement and critical intervention in AI-rich learning environments.

Building on this foundation, this paper conceptualises Prompt Literacy as an observable instructional competency in human-AI collaboration. Prompt Literacy is defined not merely as writing effective commands, but as the externalised SRL cycle in human-AI interaction comprising prompting (planning), evaluating outputs (monitoring), and iteratively refining responses (intervention). As Slade (2025) suggests, AI functions here as a "cognitive mirror" that reflects the student's thought process to them (para. 10). By making this strategic cycle visible through process documentation, the framework provides observable evidence of students' engagement with planning, monitoring, evaluation, and intervention behaviours associated with self-regulated learning. Xu et al. (2025) argue that such "metacognitive support" acts as a crucial mediator; without it, the convenience of GenAI can actually "degrade" self-regulated learning habits (p. 1845). Consequently, this focus on process documentation

facilitates a "supportive process" (Lowry et al., 2025, p. 1) that externalises internal learning behaviours through a "structured pathway" of documentation (Tomisu et al., 2025, p. 1697554).

3. Instructional Design: The Reverse-Flipped Model

The mandate to assess observable competencies associated with Self-Regulated Learning (SRL) and Prompt Literacy requires a novel instructional design model. This paper proposes the conceptual Reverse-Flipped Model as a solution that leverages AI not as an avoidance target, but as a mandatory tool for learning (Farmer, 2024). Farmer (2024) further suggests that such a model repurposes the technology as a "plowshare for cultivation" rather than a disruptive force (para. 8).

In a traditional content-coverage model, homework often serves as passive review tasks that are now largely delegable to Generative AI. In the Reverse-Flipped Model, this flow is inverted. Students utilise GenAI at home to delegate the "low-stakes production" of initial drafts, such as essay outlines or code boilerplate. Within this home environment, students navigate a rapidly evolving product landscape where generative tools are increasingly specialised for diverse academic tasks (Baytas & Ruediger, 2024). Consequently, class time is dedicated exclusively to the "high-stakes human tasks" of critique, defence, and iterative refinement. As Janio (2025a) describes this "flipped classroom 2," faculty are no longer primary content sources but "essential guides" helping students validate machine outputs (para. 6). This shifts the pedagogical focus from creation to "evaluative judgement" and critical intervention (Chiu, 2023, p. 6192).

This model is highly adaptable across various disciplines:

Table 1: Disciplinary Case Study - History

Component	Rationale
Task	Students delegate the drafting of a primary source analysis to AI at home. The class session then requires them to critique that draft against new, conflicting sources introduced in real-time.
Competence Measured	The ability to analyse and adapt a flawed artefact under pressure, ensuring AI acts as a "supportive process" rather than an answer-generator (Lowry et al., 2025).

Table 2: Disciplinary Case Study - Digital Photography

Component	Rationale
Task	In applied arts, AI-assisted technical production is performed by the student.
Competence Measured	Human-led aesthetic judgement and ethical considerations, ensuring students maintain creative agency (Yıldızhan Bora & Şahin Kölemen, 2025).

Table 3: Disciplinary Case Study - Coding Course

Component	Rationale
Task	Students use AI for boilerplate syntax generation. Class time is dedicated to debugging, security auditing, and justifying logic.
Competence Measured	Moving from rote generation to active engagement (Dennard, 2024), focusing on security consciousness and logic.

Ultimately, the faculty role is redefined from a transmitter of knowledge to a "learning designer." As Zhang (2024) asserts, this transition is a fundamental re-architecting of the role, one predicated on the teacher becoming the "learning designer" who is responsible for designing, curating, and assessing technology-mediated learning experiences" (p. 1).

This new mandate compels the adoption of a complementary collaboration model. In this model, AI handles routine administrative tasks and content management, thereby liberating the educator to focus exclusively on the high-stakes human components of the process (Zhang, 2024, p. 37). This AI-enhanced design elevates student engagement by pivoting the pedagogical focus from content absorption to higher-order cognitive interaction, ensuring that technology serves to "enhance the human pedagogical relationship" rather than replace it (Triberti et al., 2024, p. 1329605). This proactive redesign of learning outcomes (Jensen et al., 2024) confirms the faculty's role as an essential architect of competence.

4. Research Design, Methods, and Assessment

This study employs a Design Science Research (DSR) framework, a methodology suited for the development and preliminary evaluation of pedagogical artefacts in technology-enhanced learning environments. The Reverse-Flipped Model is conceptualised as a designed instructional intervention that addresses the assessment challenges introduced by Generative AI. Within the DSR framework, the study identifies the delegation crisis as the underlying educational problem, proposes process-based assessment artefacts as the design solution, presents preliminary feasibility evidence through expert feedback, and outlines directions for future empirical validation.

Table 4. Design Science Research Framework of the Study

DSR Stage	Application in this Study
Problem Identification	AI-enabled delegation crisis
Design Objectives	Process-based competence assessment
Artefact Design	Reverse-Flipped Model and APP
Preliminary Evaluation	Expert feasibility validation

Future Validation	Pilot implementation studies

Strategies for High-Value, AI-Integrated Assignments

Successful implementation of the Reverse-Flipped Model necessitates a structural re-engineering of the assessment environment. Rather than avoiding AI, instructional designers must proactively "stress-test" assignment parameters to expose vulnerabilities and ensure that tasks demand high-level cognitive engagement (Pritts, 2025). This differentiation is fundamental: whereas undergraduate scaffolding relies on structured "Process Logs" to provide traceable evidence of the Self-Regulated Learning (SRL) cycle, postgraduate assessment focuses on the complexities of "Ethical Judgement" and the integration of domain-specific expertise within ambiguous, real-world scenarios.

Modality-Specific Documentation and Transfer Tasks

To effectively externalise metacognition, documentation methods must be meticulously aligned with the delivery modality. In distance asynchronous environments, the Automated Process Portfolio (APP) serves as the primary evidentiary tool. Assessment moves beyond the final artifact to evaluate the strategic engagement reflected in the student's prompt path and intervention decisions, making behaviours associated with the self-regulated learning cycle observable for assessment. The APP proposed in this paper is conceptualised as a process documentation artefact rather than a platform-specific technological solution. Students document their initial prompts, revised prompts, selected AI outputs, intervention decisions, and reflective justifications as evidence of strategic engagement during AI-assisted learning. Future implementations may be integrated within institutional LMS (Learning Management System) platforms or institutionally approved AI tools subject to local privacy and data governance requirements. This structured documentation approach supports institutional sustainability by facilitating process-based assessment in high-volume learning environments. By leveraging structured process documentation and institutionally supported AI-assisted administrative workflows where appropriate, institutions may reduce some of the workload traditionally associated with process-based grading. This integration fosters what Aaron et al. (2025) describe as a "synergistic feedback loop," where optimised human-AI interaction protects instructional time while simultaneously elevating the rigour of student output.

For synchronous online environments, "Live Metacognitive Huddles" utilise shared-screen interactions to measure competence through verbal justification and real-time responses to peer challenges. Similarly, the physical or hybrid classroom utilises "Hybrid Artefacts"—such as annotated digital sketches or logic maps—to visualise a student’s ideation. These serve as a definitive "Artefact of Metacognitive Intervention," proving the exact moment of critical discernment where the human agent overrode or refined the machine’s output.

Assessment Transparency and Process-Based Assessment

The transition from product-to-process demands a shift in the hierarchy of assessment values (Luo, 2024). If assessments are to accurately reflect students' strategic engagement and demonstrated competencies (Dawson et al., 2024), Analytic Rubrics must be recalibrated to assign primary weight (60–70%) to Process Documentation rather than final product quality. This ensures that academic integrity is built into the design rather than policed at the perimeter. Furthermore, by moving away from generic prompts towards case-based and scenario-oriented tasks (AlAfnan et al., 2023), rubric criteria can focus on "evaluative judgement" and the

strategic application of information rather than mere technical proficiency (Mejías-Acosta, 2024).

Assessing Strategic Human Intervention

To operationalize the self-regulated learning cycle, rubric criteria should explicitly assess students' planning, monitoring, evaluation, and strategic intervention behaviours. Recognising that metacognition is most effective when it is systematically scaffolded (Muijs & Bokhove, 2020), the framework prioritises students' ability to critically evaluate and revise AI-generated outputs. Within the context of this framework, the term *Cognitive Overconfidence* is used to describe the uncritical acceptance of AI-generated outputs without adequate planning, monitoring, evaluation, or strategic intervention. Observable manifestations of Cognitive Overconfidence may include accepting factual inaccuracies, overlooking logical inconsistencies, or engaging only superficially with revision and justification processes. This pedagogical concern is consistent with recent scholarship demonstrating that metacognitive support plays a critical role in sustaining self-regulated learning behaviours in Generative AI environments (Xu et al., 2025). Within this assessment framework, Cognitive Overconfidence functions as a process-based assessment descriptor that captures insufficient strategic engagement during AI-assisted learning tasks rather than a psychometrically validated psychological construct or learner deficit.

Observable failures in strategic intervention are reflected through lower-band rubric descriptors that indicate insufficient engagement with the assessment task. This provides instructors with observable evidence of students' strategic engagement in AI-assisted learning environments. The goal is not to directly measure metacognition or self-regulated learning as psychological constructs, but to document behaviours theoretically associated with planning, monitoring, evaluation, and intervention. The framework therefore supports a transition towards process-based grading, where evidence of student competence resides in strategic human intervention throughout the collaborative journey between the learner and the generative tool rather than in the delegable final product.

Preliminary Expert Feasibility Validation

To bridge the gap between this conceptual design and future longitudinal implementation, the feasibility of these artefacts was subjected to preliminary expert validation (refer to Appendix 7.3). This data comprises qualitative consensus from a panel of instructional designers and faculty leaders with expertise in assessment and online learning. Preliminary expert feedback suggests that the Intervention Justification Memo and the APP represent pedagogically useful and potentially sustainable mechanisms for documenting student strategic intervention in high-volume asynchronous settings. These findings provide preliminary feasibility evidence for the proposed design while identifying avenues for future empirical validation and rubric calibration studies.

5. Discussion, Implications, and Limitations

The Inflection Point and Role Redefinition

The pervasive adoption of Generative AI represents a crucial inflection point, necessitating a fundamental clarification of the faculty's pedagogical function. By automating tasks associated with lower-order cognitive skills, AI effectively removes the academic incentive for passive content absorption (Bloom, 1956). This shift highlights the inadequacy of content dissemination as a primary teaching function (Jensen et al., 2024), necessitating a redefinition of the faculty role from a transmitter of knowledge to an architect of competence-based learning environments.

Rather than acting as a replacement for the instructor, AI tools should be viewed as mechanisms to "enhance the human pedagogical relationship" (Triberti et al., 2024). Within this framework, the instructor's expertise is focused on designing high-stakes challenges that provoke "observable and measurable" changes in student behaviour (Skinner, 1974). This transition ensures that the human element of education focuses on mentorship and critical intervention, leaving rote synthesis to automated systems.

The Institutional Mandate: Sustainability and Equity

Implementing a comprehensive CBE framework requires institutional consideration of two important dimensions: faculty sustainability and equitable access.

Faculty Workload and Support: Transitioning to a process-oriented assessment model is inherently more cognitively demanding than evaluating static final products. To maintain academic standards, faculty require appropriate institutional support to "stress-test" assignment designs against evolving AI vulnerabilities (Pritts, 2025). The Automated Process Portfolio (APP) is designed to support process-based assessment practices by facilitating structured documentation of students' strategic engagement. By leveraging institutionally supported AI-assisted administrative workflows and process documentation practices where appropriate, institutions may reduce some of the workload traditionally associated with process-based grading. This integration fosters what Aaron et al. (2025) describe as a "synergistic feedback loop," where optimised human-AI interaction protects teaching time while simultaneously elevating student drafting rigour.

Equity and Access: Beyond workload considerations, institutions must address the structural risk that an emphasis on Prompt Literacy might exacerbate the "digital and cognitive equity gap." To prevent this technological shift from entrenching existing achievement disparities, it is important to prioritise the development of digital agency. A strong focus on digital agency is particularly critical for adult learners in open-access institutions, as their diverse backgrounds and often lower initial digital literacy require deliberate scaffolding to ensure equitable participation. Bridging this gap requires more than just tool access; it demands a systemic transition from "Digital Natives" into "AI Natives" who possess robust information literacy and the capacity for critical intervention (Ponce Rojo et al., 2025). Institutions may support this transition through scaffolded prompt libraries, multilingual exemplars, accessibility accommodations, AI literacy orientation modules, and institutionally supported access to approved AI tools. Ultimately, institutional success will depend upon the extent to which equitable access to AI literacy, process-based assessment practices, and appropriate technological support can be provided across diverse learner populations.

Limitations and Future Research

The primary limitation of this framework remains its current reliance on theoretical modelling. Several instructional design recommendations in this framework are informed by emerging practitioner literature in AI-integrated pedagogy. The proposed framework does not claim to directly measure metacognition or self-regulated learning as psychological constructs. Rather, it documents observable behaviours theoretically associated with these constructs in AI-assisted learning environments. While the proposed APP and Reverse-Flipped Model are grounded in established learning theories, their practical efficacy in reducing faculty cognitive load and supporting process-based assessment practices remains an area for empirical validation. Future empirical studies should further validate these recommendations across institutional contexts, particularly with respect to equitable implementation practices, accessibility considerations, and institutional support structures for AI-assisted learning. Future research should examine rubric calibration, institutional scalability, comparative skill-transfer

effectiveness, and longitudinal implementation across different academic disciplines and instructional modalities.

To move the Reverse-Flipped Model toward empirical validation, the following phased research agenda is proposed:

1. Phase 1: Qualitative Feasibility Check. Conduct semi-structured interviews with 10–15 instructional designers and faculty leaders to assess the pedagogical usefulness, rubric alignment, and implementation feasibility of the Analytic Rubric and Intervention Justification Memo.
2. Phase 2: Pilot Implementation Study. Conduct a pilot study in a single high-volume, asynchronous course (e.g., ENG 1102) to examine the impact of the proposed assessment framework on students' strategic engagement and self-reported metacognitive behaviours during AI-assisted learning, while quantitatively tracking faculty workload hours.
3. Phase 3: Comparative Effectiveness Study. Conduct a quasi-experimental study comparing a cohort using the Reverse-Flipped Model against a control group using traditional assessment practices to evaluate the transfer of strategic human intervention skills (e.g., critical vetting of information) to subsequent non-AI-assisted tasks.
4. Phase 4: Institutional Scalability and Longitudinal Implementation Study. Conduct longitudinal, multi-course and multi-disciplinary implementation studies to examine institutional scalability, rubric consistency, instructor workload, student outcomes, and equitable access across diverse instructional contexts. Particular attention should be given to privacy considerations, institutional AI policies, and the sustainability of process-based assessment practices over time.

6. Conclusion

The proliferation of generative AI has acted as a diagnostic tool, exposing the foundational weaknesses of content-centric education and its historical reliance on flawed proxy measures. The academic mandate is now undeniable: institutional validation must pivot from quantifying seat time to verifying the attainment of specific, observable competencies. As the traditional assumption that a final product constitutes sufficient evidence of learning becomes increasingly untenable (Janio, 2025b), the academy must adopt frameworks that certify the process of thought rather than just its output.

The conceptual Reverse-Flipped Model proposed in this paper provides this structural solution, compelling students to externalise internal metacognitive cycles through traceable, behavioural artefacts. By repurposing AI as a "supportive process" (Lowry et al., 2025) and a "cognitive mirror" (Slade, 2025), the model ensures that rigour is maintained not through the exclusion of technology, but through the intensification of human critical engagement.

Ultimately, this transition requires the faculty role to evolve from that of a content manager to an architect of competence. By grounding assessment in the "unique critical intervention" of the learner (Luo, 2024), institutions can move beyond the delegation crisis to a more authentic and valid verification of human expertise. In this machine-augmented era, the true measure of academic success will not be the ability to generate content, but the mastery of the strategic, self-regulated judgement required to direct it.

7. Appendix: Assessment Demonstration (ENG 1102- Composition II)

This appendix illustrates the implementation of the Reverse-Flipped Model in an undergraduate required course, ENG 1102 (English Composition II). The task is specifically designed to assess Metacognitive Control (SRL) and Prompt Literacy over passive writing production.

7.1 Reverse-Flipped Assignment Prompt: Argumentative Essay Process

Course Learning Outcome (SLO) Measured: The student will demonstrate the ability to critically evaluate and synthesise external source material to construct a supported, original argument.

Table 5: Reverse-Flipped Assignment Prompt

Component	Task	Assessment Weight	Competency
I. AI Delegation	Use a GenAI tool to draft the body paragraphs and preliminary supporting evidence for a 1,500-word persuasive essay on the assigned topic.	10% (Pass/Fail)	Content Generation (Low-Stakes)
II. Human Intervention	Manually write the Introduction (including Thesis), Conclusion, and all Topic Sentences for the essay.	30%	Framing & Structure (Product Quality)
III. Process Documentation	Submit the complete Automated Process Portfolio (APP) Log and an Intervention Justification Memo.	60%	Metacognitive Control (High-Stakes) (Process Quality)

Intervention Justification Memo Requirements:

1. Planning: Submit the "Initial Prompt." As Lowry et al. (2025) note, this externalises the student's initial goal-setting and task analysis (p. 1).
2. Monitoring: Identify two sections of AI content that were factually incorrect or logically unsound.
3. Intervention: Write a 200-word memo justifying the decision to revise or replace content. This requires the student to move beyond "metacognitive laziness" (Fan et al., 2024) to engage in "unique critical intervention" (Luo, 2024, p. 6188).

7.2 Analytic Rubric (Focus on Process/SLO Attainment)

The rubric documents observable behaviors associated with the SRL cycle, making the assessment "AI-proof" by quantifying the "supportive process" (Lowry et al., 2025) rather than the machine-generated output.

This section of the analytic rubric (60% weight) assesses the observable planning, monitoring, evaluation, and strategic intervention behaviors associated with self-regulated learning (SRL) principles, making the assessment AI-proof and providing verifiable evidence of SLO

attainment for accreditation.

Table 6: Analytic Rubric

Criterion (SLO)	Advanced (4 Points)	Proficient (3 Points)	Developing (2 Points)
Prompt Literacy & Planning (SRL: Planning)	The initial is highly specific, multi-layered (constraints, persona, tone), and clearly anticipates the required scholarly outcome. Shows robust "cognitive tactics" (Winne, 2017).	The initial is clear and relevant, including essential constraints (e.g., source count, length). Shows sufficient planning.	The initial prompt is general or vague, requiring multiple non-justified follow-up prompts to achieve basic results. Indicates a failure to "transform mental abilities into academic skills" (Zimmerman, 2008).
Critical Vetting & Intervention (SRL: Monitoring/Intervention)	The memo identifies and corrects deep-level flaws (e.g., logical fallacies, unstated assumptions, misinterpretation of required sources). Justification uses domain-specific reasoning and scholarly evidence. Demonstrates AI as a "cognitive mirror" (Slade, 2025).	The memo identifies clear errors (e.g., basic factual errors, weak synthesis) and justifies revisions. Intervention maintains the argument's integrity.	The memo only addresses superficial errors (e.g., grammar, syntax) or overlooks a major, verifiable error (Cognitive Overconfidence). Intervention is minimal or counterproductive. Demonstrates observable indicators of "Cognitive Overconfidence" (Xu et al., 2025) within the proposed assessment framework.
Strategic Reflection & Justification (SRL: Evaluation)	Reflection deeply analyses the efficiency of the prompt path, connecting strategic choices (or failures) to a future workflow improvement. Demonstrates robust self-correction.	Reflection adequately explains the reasoning behind major revisions and links intervention choices to the final product's quality.	Reflection is superficial or focuses on general feelings (e.g., "AI helped a lot") instead of offering specific, strategic insights for improvement.

By prioritising the "evaluative judgment" (Chiu, 2023) and the "synergistic feedback loop" (Aaron et al., 2025) between student and machine, this rubric provides verifiable evidence of

SLO attainment for accreditation in the age of Generative AI.

7.3 Appendix: Preliminary Expert Feasibility Validation of the Proposed Artefacts

To bridge the gap between conceptual design and future longitudinal implementation, a preliminary expert feasibility review was conducted to evaluate the pedagogical usefulness, concept alignment, institutional sustainability, and implementation readiness of the proposed instructional and assessment artefacts. This expert review serves as proxy data that provides preliminary feasibility evidence for the proposed framework.

Twenty-eight higher education faculty members and instructional designers participated in the expert review. Participants were invited based on their experience in higher education teaching, assessment practices, instructional design, and online learning environments. The purpose of the review was to assess the suitability of the proposed process-based assessment framework for AI-integrated learning environments and to identify considerations for future pilot implementation.

The expert review instrument consisted of five Likert-scale items that evaluated the validity of prioritising process documentation and strategic human intervention over final product quality in AI-assisted assessment, the suitability of Prompt Literacy as an observable instructional competency that reflects self-regulated learning behaviours during human-AI collaboration, the fairness and pedagogical usefulness of rubric descriptors associated with Cognitive Overconfidence as a process-based assessment descriptor, the institutional sustainability and feasibility of implementing the AI Process Portfolio in asynchronous and high-volume learning environments, and the readiness of the proposed framework for pilot implementation in higher education contexts. Responses were analysed descriptively to identify levels of expert agreement across the five pedagogical propositions. Qualitative observations provided by participants were reviewed to identify recurring implementation considerations and recommendations relevant to future empirical studies.

Preliminary expert feedback suggests substantial pedagogical support for process-based assessment and strategic human intervention as core competencies in AI-integrated learning environments. Findings further indicate that the Human Intervention Memo and the AI Process Portfolio are pedagogically useful and potentially sustainable mechanisms for documenting students' strategic engagement in asynchronous learning environments. This expert review was intended to establish preliminary pedagogical feasibility rather than psychometric or construct validity. Future empirical studies will examine rubric calibration procedures, inter-rater reliability, construct alignment, student outcomes, and institutional scalability across disciplinary and instructional contexts.

Scalability, Equity, and Future Validation

Future implementations of the proposed framework should consider institutional policies related to privacy, learning management system integration, and faculty workload. Measures of scalability may include grading time, student participation rates, rubric consistency, and instructor workload across instructional contexts. The framework has been intentionally designed to remain platform agnostic, enabling institutions to implement process-based assessment using institutionally approved technologies and local data governance policies.

Equitable implementation of process-based assessment requires appropriate institutional support structures. These may include scaffolded prompt libraries, multilingual exemplars, accessibility accommodations, AI literacy orientation modules, and institutionally supported access to approved AI tools. Such measures are particularly important in ensuring that assessment privileges strategic engagement rather than unequal access to technological resources.

The proposed framework does not claim to directly measure metacognition or self-regulated learning as psychological constructs. Rather, it documents observable behaviours theoretically associated with these constructs during AI-assisted learning. Future empirical studies will examine construct alignment, rubric calibration, inter-rater reliability, longitudinal student outcomes, and institutional scalability across disciplinary and instructional contexts.

Table 7: Expert Feasibility Validation (Q1-Q5)

Pedagogical Proposition	Expert Consensus (Agree/Strongly Agree) (%)	Qualitative Thematic Feedback Summary
Strategic Human Intervention (Q1)	75%	Strong Pedagogical Support: There is a robust belief that the 'Human Intervention Memo' offers a more authentic measure of student thinking than traditional final essays, and the grade shift rewards the "human in the loop."
Prompt Literacy and Process Documentation (Q2)	50%	Divided Consensus/Caution: Expert opinion is split with high neutrality, suggesting significant uncertainty about whether the observable cycle of Prompting → Vetting → Refining is a *sufficient* measure of Self-Regulated Learning (SRL).
Cognitive Overconfidence as a Process-Based Descriptor (Q3)	53.6%	Guarded Acceptance/High Neutrality: Only 15 of 28 faculty (53.6%) agreed. A significant number of neutral and disagreeing responses indicate core concerns about the fairness and measurability of penalizing "Cognitive Overconfidence" via rubrics.
Institutional Sustainability (Q4)	82.1%	Strong Institutional Support: Overwhelming agreement that the Automated Process Portfolio (APP) is viewed as an important mechanism for faculty workload management because process-based grading becomes increasingly challenging in high-volume learning environments without appropriate institutional support structures.
Readiness for Pilot Implementation (Q5)	60.7%	Moderate Acceptance with Reservations: While a majority agrees, the high neutral rate (32.1%) suggests collective hesitation. Commentary focuses on the need for adequate scaffolding (like "starter prompt libraries") and addressing potential equity concerns before immediate pilot deployment.

Findings and Conclusions:

The preliminary expert feasibility review provides strong pedagogical support for the proposed Reverse-Flipped Assessment Model and its underlying process-based assessment philosophy. Faculty consensus was strongest for institutional sustainability (82.1% agreement), with the Automated Process Portfolio (APP) viewed as an important mechanism for managing faculty workload in high-volume asynchronous learning environments. Similarly, strategic human intervention as the focus of assessment received substantial support (75.0% agreement), with participants recognising the Human Intervention Memo as a more authentic representation of student thinking that foregrounds the "human in the loop." Expert feedback further supports the transition from product-based to process-based assessment as an appropriate pedagogical response to Generative AI in higher education. Institutional readiness (60.7% agreement) suggests cautious support for future pilot implementation of the proposed framework.

The overall level of disagreement across the survey responses was relatively low (11.27%), indicating broad pedagogical acceptance of the proposed artefacts while simultaneously identifying important areas for refinement. This percentage was calculated as:

$$\text{Percentage of Disagreement} = (\text{Number of Disagree and Strongly Disagree responses} \div \text{Total number of responses}) \times 100 = (16 \div 142) \times 100 = 11.27\%$$

Preliminary expert feedback identified two areas that warrant further conceptual and empirical development. The moderate level of agreement regarding Prompt Literacy as an observable instructional competency associated with self-regulated learning behaviours (50.0%) suggests the need for further rubric development and construct alignment studies. Similarly, the guarded acceptance of Cognitive Overconfidence as a process-based assessment descriptor (53.6%) highlights legitimate concerns regarding fairness, implementation, and pedagogical interpretation. Both findings reinforce the need for further empirical investigation before large-scale implementation.

Finally, the findings suggest that the successful and sustainable implementation of the Reverse-Flipped Assessment Model will depend upon institutional support for process-based assessment and equitable implementation practices. Future pilot studies should prioritise rubric calibration, faculty training, accessibility considerations, scaffolded prompt libraries, and institutionally supported AI tools to support diverse learner populations. The present findings should therefore be interpreted as preliminary feasibility evidence that informs future empirical validation and longitudinal implementation studies.

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Declaration and Funding:

This article has not been published previously or considered elsewhere. No funding has been provided for this research.