RESEARCH ARTICLE

Navigating Generative AI in the Classroom: A Three-Tier Decision Framework for Assignment Design in Higher Education

Sandra Mulzer[1] (smulzer@bradley.edu), Jessica Williams[1] (jwilliams@bradley.edu)

[1]Foster College of Business, Bradley University, Peoria, IL, United States

Abstract

Generative artificial intelligence (AI) tools have changed the practical conditions under which many higher education assignments are completed. Instructors now need assignment-level guidance that is more precise than a course-wide ban or a course-wide permission statement. This paper proposes a Three-Tier Decision Framework for aligning permissible AI use with learning objectives. The framework classifies assignments by two features: (1) the cognitive complexity required by the task, using established taxonomies of educational objectives, and (2) the extent to which the task develops discipline-specific professional practice. These dimensions lead to three recommended levels of AI integration: Restricted (Tier 1), where AI use would bypass foundational learning; Guided (Tier 2), where AI can support the work under explicit instructor-defined constraints; and Open (Tier 3), where effective human–AI collaboration is part of the intended competency. The framework was refined through structured feedback sessions with 63 faculty members across four institutions and piloted with 214 undergraduate students in business and computing courses. In the pilot, students reported a clearer understanding of AI-use expectations than they had experienced under prior undifferentiated course policies, and instructors reported fewer ambiguous academic-integrity conversations. Because the pilot was exploratory and relied partly on self-report, the results should be interpreted as preliminary. The paper discusses implications for assignment design, academic-integrity communication, curriculum sequencing, and future empirical validation.

Keywords — Generative Artificial Intelligence; Assignment Design; Higher Education; Educational Framework; Academic Integrity

1 Introduction

Publicly accessible generative artificial intelligence (AI) tools have made assignment design a more immediate concern in higher education [1, 2]. Large language models can draft essays, solve many routine quantitative problems, generate code, and summarize complex texts at a level that is sufficient for many undergraduate tasks [3]. As a result, instructors must now ask whether a given assignment still elicits the learning process it was designed to assess.

Institutional responses have varied widely. Some universities issued blanket prohibitions, treating any undisclosed use of generative AI as a violation of academic honesty codes [4]. Others adopted permissive stances, reasoning that students will inevitably use these tools in professional settings and should therefore learn to wield them effectively [5]. A smaller number of institutions attempted middle-ground policies, but these often amounted to vague directives such as, “use AI responsibly”, that left both faculty and students uncertain about expectations [6].

The difficulty with all three stances is that they treat the relationship between generative AI and learning as uniform across assignments. In reality, the appropriateness of AI assistance depends heavily on what a given assignment is trying to accomplish. An exercise designed to build foundational writing skills occupies a fundamentally different pedagogical space than a capstone project in which students integrate multiple competencies and use professional tools. A policy that is sensible for one may be counterproductive for the other.

This paper introduces a *Three-Tier Decision Framework* that addresses this gap by linking the permissible level of AI integration to two observable characteristics of assignments: the cognitive complexity of the task and the extent to which the task targets discipline-specific professional competencies. Rather than asking the binary question “should students use AI?” the framework asks “what kind of AI engagement, if any, serves the learning objective of this particular assignment?”

The remainder of the paper is structured as follows. Section 2 reviews the relevant literature on AI in education, academic integrity challenges, and existing frameworks for technology integration in the classroom. Section 3 presents the Three-Tier Decision Framework in detail. Section 4 describes the iterative development process, including faculty feedback sessions and a student pilot. Section 5 discusses implications for practice and compares the framework to alternative approaches. Section **??** outlines directions for future research, and Section 6 concludes the paper.

2 Related Wrok

The application of artificial intelligence to education predates the current wave of generative models by several decades. Intelligent tutoring systems, adaptive learning platforms, and automated essay scoring tools have been explored since at least the 1990s [7]. The work in [8] conducted a systematic review of AI applications in higher

Submitted: April 20, 2025 Accepted: May 3, 2025 Published: May 18, 2025
www.pearlacademicpublishing.com

education and found that much of the research had focused on student-facing tools, including recommendation engines, chatbots for administrative queries, and plagiarism detection software, while comparatively little attention had been given to how AI changes the design of assessment itself.

The work in [9] warned early on that AI would eventually force a re-examination of what it means to demonstrate competence. It argued that when machines can perform routine cognitive tasks, the value of assessing those tasks in isolation diminishes. This argument has gained considerable urgency since the release of publicly available large language models, which can produce text, code, and analytical outputs that are difficult to distinguish from student-generated work [10].

Academic integrity has been a concern in higher education long before AI entered the conversation. Prior work [11] documented widespread cheating across North American universities, finding that contextual factors, including peer norms, perceived risk of detection, and the instructor's investment in the course, were stronger predictors of dishonest behavior than individual moral dispositions. Subsequent work [12] extended this line of inquiry to contract cheating, demonstrating that commercial essay mills exploited the same contextual vulnerabilities.

The introduction of generative AI has added a new dimension to these long-standing concerns. Unlike contract cheating, which involves a deliberate transaction with a third party, the use of a freely available AI tool can occur on a spectrum from outright substitution to legitimate assistance [4]. The work in [6] observed that many students genuinely do not understand where the boundary lies, particularly when institutional policies are ambiguous. This ambiguity is compounded by cultural variation in norms around collaboration and originality, a factor well documented in the pre-AI literature on international student plagiarism [12].

The taxonomy of educational objectives originally proposed in [13] and later revised in [14] remains one of the most widely used frameworks for classifying learning tasks. The revised taxonomy arranges cognitive processes along a continuum from lower-order skills (remembering, understanding) through intermediate skills (applying, analyzing) to higher-order skills (evaluating, creating).

Several works have noted that generative AI performs unevenly across this continuum. Tools such as large language models excel at tasks that require recall, summarization, and formulaic application but struggle with tasks that demand genuine evaluation, synthesis of novel ideas, or creative problem-solving in unfamiliar domains [1, 2]. The work in [3] built on this observation to propose seven assignment archetypes that vary in the degree of AI involvement, from AI-as-tutor to AI-as-collaborator. While this work has been influential, it focuses primarily on the instructor's intention rather than on the structural characteristics of the assignment itself.

A parallel strand of literature emphasizes that graduates must be prepared for workplaces in which AI tools are already reshaping job tasks. The work in [15] argued that management educators face a paradox: shielding students from AI may protect the integrity of current assessments but leave graduates unprepared for the labor market. The information systems discipline, in particular, has grappled with this tension, as evidenced by [16], which identified workforce readiness as one of three pressing challenges that AI poses for IS education.

The work in [17] surveyed the state of AI integration in higher education and found that the most successful implementations were those in which AI use was explicitly aligned with stated learning outcomes. The study cautioned against what it termed "tool-first" adoption, in which technology drives pedagogy rather than the reverse. This finding reinforces the need for a principled framework that begins with learning objectives and derives the appropriate level of AI involvement from them.

Several frameworks have been proposed for integrating AI into educational settings, though many operate at the level of broad principles rather than at the level of assignment design. The work in [18] framed generative AI as a student-driven innovation and argued that higher education should reconsider how learning activities and assessment practices respond to student use of these tools. The present framework addresses a narrower question: how an instructor can decide, assignment by assignment, what forms of AI use are pedagogically appropriate.

The work in [19] conducted a critical review of how AI is discursively framed in the higher education literature and identified four dominant narratives: AI as a threat, AI as an opportunity, AI as inevitable, and AI as a partner. It urged researchers to move beyond these broad framings toward context-specific guidance. The Three-Tier Decision Framework responds to this call by anchoring guidance in the observable characteristics of individual assignments rather than in institution-wide narratives.

3 The Three-Tier Decision Framework

The framework rests on two premises derived from the literature reviewed above. First, the appropriateness of generative AI integration depends on the cognitive complexity of the learning task, as captured by established taxonomies of educational objectives [13, 14]. Second, it depends on whether the assignment targets discipline-specific professional competencies for which AI fluency is itself a workforce requirement [15, 16].

These two dimensions, that is, cognitive complexity and professional competency orientation, are conceptually independent. A low-complexity drill in vocabulary recall targets a foundational skill irrespective of professional context. Conversely, a professionally oriented capstone project may involve tasks at multiple levels of complexity.

Table 1: Three-Tier Decision Framework: mapping assignment characteristics to recommended AI integration level.

Cognitive Complexity	Competency Orientation	Tier	Recommended AI Integration
Low	Foundation	Tier 1 (Restricted)	AI use prohibited or heavily restricted; assessment targets skill acquisition that AI would bypass.
Low	Practice	Tier 2 (Guided)	AI use permitted under faculty-defined constraints; students learn to evaluate and verify AI outputs.
Moderate	Foundation	Tier 1 (Restricted)	AI use restricted; students must demonstrate independent analytical reasoning.
Moderate	Practice	Tier 2 (Guided)	AI used as scaffolding; students must document AI interactions and critically assess outputs.
High	Foundation	Tier 2 (Guided)	AI may be used for preliminary research or drafting under strict disclosure; final product must reflect original thought.
High	Practice	Tier 3 (Open)	AI use actively encouraged; AI fluency is a learning objective; assessment focuses on integration quality and critical judgment.

The framework uses the conjunction of these two dimensions to classify assignments into one of three tiers of recommended AI integration.

3.1 The Dimensions

Drawing on the revised Bloom's taxonomy [14], cognitive complexity is operationalized as a three-level ordinal scale:

- **Low complexity.** Tasks that primarily require remembering, understanding, or routine application of established procedures. Examples include definitional quizzes, basic programming exercises with well-defined specifications, and short-answer recall questions.
- **Moderate complexity.** Tasks that require analysis, comparison, or the application of concepts to unfamiliar contexts. Examples include case study analyses, data interpretation exercises, and structured research summaries.
- **High complexity.** Tasks that require evaluation of competing alternatives, synthesis of multiple knowledge domains, or creation of novel artifacts. Examples include original research proposals, system design projects, and position papers that integrate evidence from multiple sources.

Professional competency orientation reflects the extent to which the assignment prepares students for specific workplace tasks in which AI tools are already standard practice or are expected to become so. This dimension is operationalized as a binary distinction:

- **Foundation-oriented.** The assignment targets fundamental disciplinary knowledge or transferable academic skills (e.g., writing, mathematical reasoning, critical reading) that underpin professional competence but are not themselves professional tasks.
- **Practice-oriented.** The assignment simulates or directly engages professional tasks in which the use of AI tools is expected or valued by employers (e.g., automated report generation, AI-assisted data analysis, prompt engineering for business applications).

3.2 The Three Tiers

The intersection of these two dimensions produces the tiered structure summarized in Table 1 and illustrated schematically in Fig. 1.

3.2.1 Tier 1: Restricted AI Integration

Tier 1 applies to assignments where the primary learning objective is the acquisition of foundational knowledge or skills that generative AI would effectively bypass. The pedagogical rationale is straightforward: if a student can

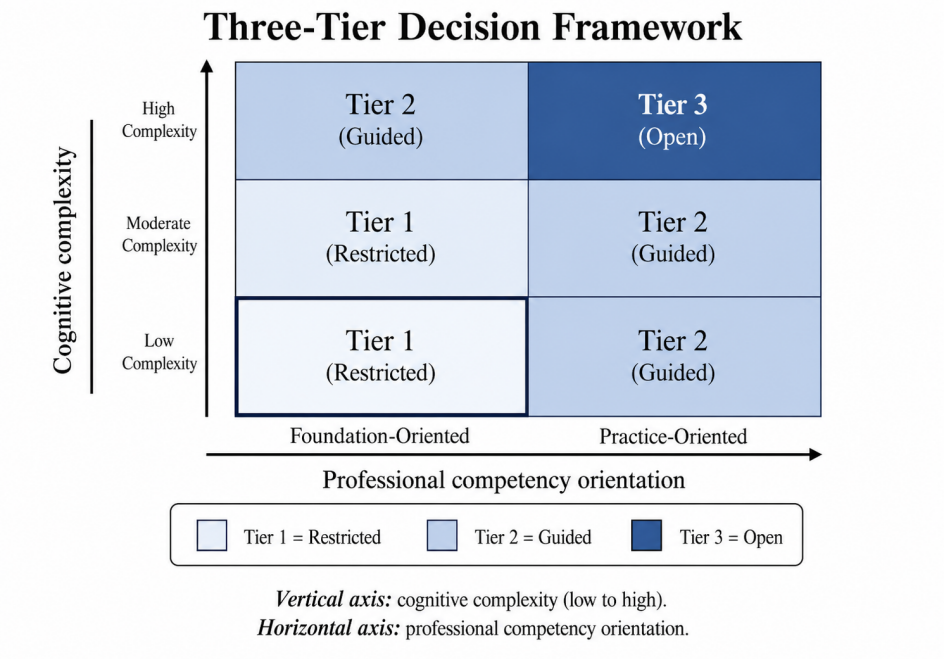


Figure 1: Schematic representation of the Three-Tier Decision Framework. Tier 1 assignments (Restricted) appear in the lower-left region, Tier 2 (Guided) assignments occupy intermediate cells, and Tier 3 (Open) assignments appear in the upper-right corner.

obtain a correct answer by prompting an AI tool without engaging in the cognitive process the assignment was designed to exercise, then the assignment fails to serve its purpose.

Examples of Tier 1 assignments include introductory programming exercises in which the objective is for students to practice writing code from scratch; definitional examinations that test recall of core terminology; and structured writing exercises in composition courses where the goal is to develop sentence-level fluency. In each case, the value of the assignment lies in the process, not the product.

Faculty implementing Tier 1 restrictions should pair the restriction with clear communication about why the restriction exists. Prior research has consistently shown that students are more likely to comply with academic integrity expectations when they understand the pedagogical reasoning behind them [6, 11]. Practical enforcement mechanisms such as proctored in-class assessments, handwritten components, or oral defenses, can supplement policy-based restrictions.

3.2.2 Tier 2: Guided AI Integration

Tier 2 applies to assignments in which AI can serve as a legitimate scaffold or productivity aid, but the learning objective still requires students to exercise independent judgment. This is the broadest tier and applies to the majority of assignments in most curricula.

In a Tier 2 assignment, faculty define explicit constraints on how AI may be used. These constraints might include requirements to disclose all AI interactions, to submit prompt logs alongside final deliverables, to annotate AI-generated content with critical commentary, or to use AI only for specified subtasks (e.g., literature search but not argumentation). The key principle is that the student must add substantial intellectual value beyond what the AI produces.

Mollick and Mollick [3] provide useful precedent here with their concept of "AI-as-coach," in which students use AI to receive feedback on drafts but are responsible for revision and final argumentation. Tier 2 extends this idea by making the constraints assignment-specific rather than course-wide, thereby accommodating the heterogeneity of learning objectives within a single course.

3.2.3 Tier 3: Open AI Integration

Tier 3 applies to assignments where AI fluency is itself a learning objective. These assignments are typically practice-oriented and cognitively complex: they simulate professional tasks in which effective use of AI tools is a valued competency.

Examples include capstone projects in information systems where students build AI-augmented business solutions; data science assignments in which students use AI to automate portions of an analytical pipeline and

Table 2: Illustrative rubric dimensions for a Tier 3 (Open) assignment in which AI fluency is a learning objective.

Criterion	Exceeds (A)	Meets (B–C)	Below (D–F)
Prompt Design	Prompts are iteratively refined, well-structured, and strategically tailored to the task.	Prompts are functional but show limited iteration or strategic awareness.	Prompts are vague, generic, or copied from external sources without adaptation.
Critical Evaluation of AI Output	Student identifies and corrects errors, biases, or gaps in AI-generated content with evidence.	Student notes some limitations but does not systematically verify claims.	Student accepts AI output uncritically; errors propagated to final deliverable.
Integration with Original Analysis	AI output is seamlessly woven into a coherent, original argument with clear attribution.	AI output is present alongside original work but integration is uneven.	Final product is predominantly AI-generated with minimal original contribution.
Reflection and Transparency	Detailed prompt log and reflective commentary demonstrate metacognitive awareness of AI use.	Prompt log is present but reflection is superficial.	No prompt log or disclosure of AI use.

then evaluate the quality of the output; and business communication exercises in which students use AI drafting tools and then refine the output for audience, tone, and strategic messaging.

In Tier 3 assignments, assessment shifts from the product in isolation to the quality of the human–AI collaboration. Rubrics should evaluate the student's ability to formulate effective prompts, critically assess AI outputs, identify errors or biases in generated content, and integrate AI outputs with original analysis. Table 2 illustrates a sample rubric structure for a Tier 3 assignment.

4 Framework Development Process

4.1 Phase 1: Literature Synthesis and Initial Design

The initial version of the framework was developed through the literature review described in Section 2 and through the author team's teaching experience in courses where generative AI had already affected assignment design. The two dimensions considered in the framework emerged from a thematic analysis of recurring concerns in the literature: the observation that AI disproportionately threatens assessments at lower cognitive levels [1], and the recognition that workforce expectations increasingly include AI competency [15, 16].

The choice of a three-tier structure rather than a binary allow/prohibit distinction was motivated by the practical observation that most courses contain a mix of assignment types, and a single policy applied uniformly across all assignments would inevitably misalign with some learning objectives [20].

4.2 Phase 2: Faculty Feedback Sessions

To refine the framework, we conducted structured feedback sessions with 63 faculty members across four institutions during the spring and summer of 2024. Participants were drawn from departments of information systems, computer science, business administration, and English composition. Each session lasted approximately 90 minutes and followed a semi-structured format: the framework was presented, participants were asked to classify five of their own assignments into the three tiers, and a facilitated discussion followed.

Several refinements emerged from these sessions. First, faculty consistently requested clearer guidance on the boundary between Tier 1 and Tier 2 for moderate-complexity, foundation-oriented assignments. In the initial version of the framework, these assignments were assigned to Tier 1 by default, but several faculty members argued that certain forms of AI scaffolding (e.g., using AI to check grammar in a foreign-language writing course) could support rather than undermine the learning objective. We addressed this by clarifying that the "restricted" designation in Tier 1 permits limited, faculty-specified exceptions when the AI use supports a secondary learning objective without compromising the primary one.

Second, faculty in professionally oriented programs (information systems, data science) emphasized that even low-complexity assignments could benefit from Tier 2 treatment when they occur late in the curriculum and students have already demonstrated foundational competence. This feedback led to the addition of a contextual

note in the framework acknowledging that prior demonstrated mastery of the underlying skill may warrant shifting an assignment from Tier 1 to Tier 2.

Third, composition and humanities faculty noted that the "professional competency orientation" dimension, as initially defined, mapped less intuitively onto their disciplines. We revised the description of practice-oriented assignments to encompass any task that simulates activities students will perform in graduate study or professional life, not only industry tasks.

4.3 Phase 3: Student Pilot

Following the faculty feedback sessions, we piloted the framework with 214 undergraduate students across four courses at two institutions during the fall 2024 semester. The courses were: Introduction to Management Information Systems (78 students, one section), Business Communication (52 students, two sections), Intermediate Programming (44 students, one section), and Data Analytics for Business (40 students, one section).

In each course, the instructor introduced the Three-Tier Framework at the start of the semester and labeled every assignment with its tier designation and a brief rationale. At the end of the semester, students completed an anonymous survey assessing their understanding of the AI policy, their perceived fairness of the tiered approach, and their self-reported compliance. The pilot was designed as a formative evaluation rather than as a controlled effectiveness study; therefore, the survey results are used here to refine the framework and identify implementation issues, not to establish causal effects.

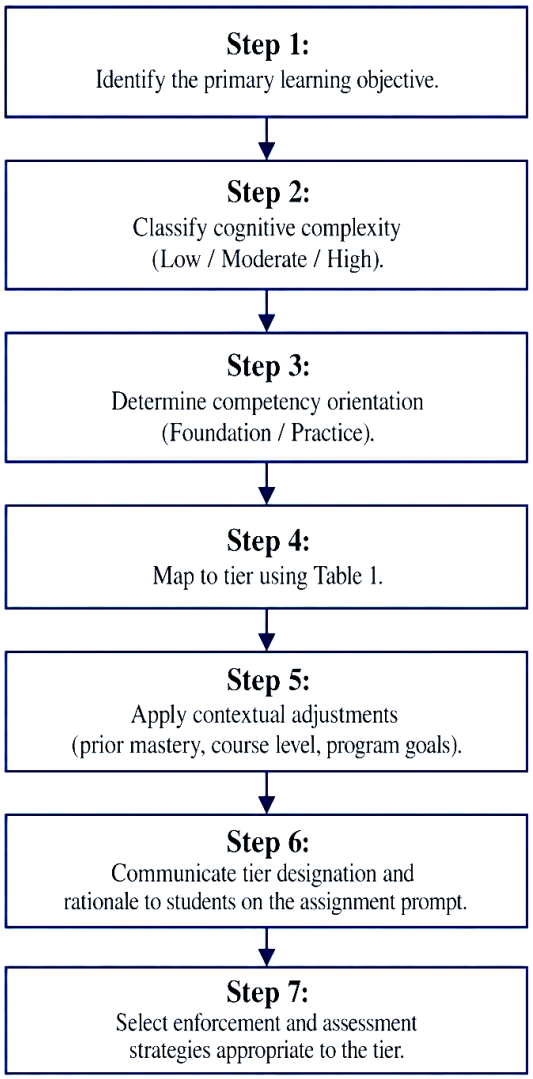


Figure 2: Decision flowchart for classifying individual assignments into tiers. Faculty begin by identifying the learning objective and proceed through a sequence of classification and contextual adjustment steps.

The pilot produced several preliminary observations. Among the 214 students, 83% reported that the tiered

labeling helped them understand the instructor's expectations regarding AI use, compared with 47% who, in a retrospective survey item, reported clear understanding under the previous semester's undifferentiated AI policies. Students in the Data Analytics course, where several assignments were designated Tier 3, reported the highest satisfaction with the policy (mean 4.2 on a 5-point scale), while students in the Intermediate Programming course, where most assignments were Tier 1, reported the lowest satisfaction (mean 3.4). Qualitative comments from the programming students revealed that the dissatisfaction stemmed not from the restriction itself but from the desire for more Tier 2 assignments in which they could practice using AI as a debugging aid.

From the faculty perspective, the four pilot instructors reported fewer ambiguous academic-integrity conversations than they had experienced in the prior academic year. One instructor noted: "In the previous year, I had six cases where I suspected AI use but couldn't determine whether the student was violating policy because the policy was too vague. This semester, with clear tier labels, I had two cases, and in both cases the student acknowledged using AI on a Tier 1 assignment and said they hadn't realized it was restricted for that assignment. The conversation was much more productive."

5 Discussion

The Three-Tier Decision Framework differs from prior approaches in several important respects. Unlike institution-wide bans or blanket permissions, it operates at the level of individual assignments, thereby accommodating the reality that a single course often contains tasks with different pedagogical purposes [19]. Unlike Mollick and Mollick's [3] seven-archetype model, which is organized around instructor intentions, the Three-Tier Framework is organized around observable assignment characteristics, making it easier for different instructors to arrive at consistent classifications for similar tasks. It also complements Dai et al.'s [18] emphasis on student-driven innovation by translating the broader call for assessment redesign into an assignment-level classification process.

This focus on the pedagogical level is both a strength and a limitation. It means the framework provides concrete, actionable guidance for assignment design, but it does not address broader institutional questions such as how to train faculty, how to update honor codes, or how to ensure equity of access to AI tools. These systemic concerns are real and important, and they require complementary institutional action [21, 22].

One of the framework's core claims is that generative AI poses a greater threat to the validity of assessment at lower levels of cognitive complexity. This claim is supported by the emerging empirical literature on AI performance across task types [1, 10], but it requires an important caveat: the capability frontier of generative AI is shifting rapidly. Tasks that were beyond AI capability in early 2023 may be routine for models released in late 2024. Faculty who use the framework must therefore revisit their tier classifications periodically, particularly for assignments in the Tier 1-Tier 2 boundary zone.

A related nuance is that cognitive complexity is not intrinsic to a topic but to a task. The same topic, e.g., database normalization, can be assessed at low complexity ("define third normal form"), moderate complexity ("normalize this unnormalized dataset and justify your decisions"), or high complexity ("design a database schema for a novel business scenario, defend your normalization choices, and evaluate the tradeoffs"). The framework classifies assignments, not subjects.

5.1 Professional Competency and the Workforce Argument

The inclusion of professional competency orientation as the second dimension reflects the growing consensus that higher education must prepare students for workplaces in which AI is already embedded [15–17]. However, this dimension introduces a tension that deserves explicit acknowledgment: the workforce argument can be used to justify premature adoption of AI in contexts where foundational learning has not yet occurred. A first-year student who uses AI to complete a basic writing assignment may gain efficiency but also fail to develop the compositional skills needed to use AI effectively in later, more complex tasks.

The framework addresses this tension by requiring that the Tier 3 designation be reserved for assignments that are both high in cognitive complexity and practice-oriented. This guards against the scenario in which AI is introduced too early in the learning sequence, before students have built the foundational competencies needed to evaluate and improve AI outputs.

A recurring theme in the academic integrity literature is that clear communication of expectations reduces the incidence of both intentional and unintentional misconduct [6, 11, 12]. The tiered labeling system directly targets this mechanism. By attaching a tier designation and rationale to each assignment, instructors make the boundary between acceptable and unacceptable AI use explicit at the point of task assignment, rather than relying on a general syllabus statement that students may not remember or may interpret differently from the instructor.

The exploratory pilot data are consistent with this expectation. The sharp increase in students who reported understanding the AI policy (from 47% under prior policies to 83% under the tiered approach) suggests that specificity matters. Future research with larger samples and controlled comparisons will be needed to confirm whether this improved understanding translates into reduced misconduct.

6 Conclusion

Generative AI has made the question of "when to use AI" a practical assignment-design issue for both faculty and students. Binary policies such as outright bans or unrestricted permissions, fail to account for the wide variation in learning objectives across different assignments. The Three-Tier Decision Framework introduced in this paper offers a middle path by connecting the level of permissible AI integration to two observable characteristics of each assignment: cognitive complexity and professional competency orientation.

The framework distinguishes three levels of integration: Restricted (Tier 1), where AI use would undermine foundational skill acquisition; Guided (Tier 2), where AI serves as a scaffold under explicit constraints; and Open (Tier 3), where AI fluency is itself a learning objective. Faculty feedback sessions and a student pilot suggest that the tiered approach improves clarity of expectations and reduces ambiguity in academic integrity enforcement, though rigorous empirical validation remains a priority for future work.

As AI tools continue to evolve, frameworks for their educational integration must evolve as well. The Three-Tier Decision Framework is therefore best understood as a structured starting point rather than a permanent rule set. For instructors and institutions, the central task is to keep AI-use policies tied to learning objectives rather than to the capabilities of any single tool.

Several directions for future research emerge from this work. First, the framework needs empirical validation through controlled studies that compare learning outcomes and academic integrity incident rates across courses that adopt the tiered approach versus those that use uniform AI policies. Such studies should include objective measures of student learning (e.g., proctored examinations) alongside subjective measures (e.g., student and faculty perceptions).

Second, the framework's second dimension (i.e., professional competency orientation) would benefit from further operationalization, particularly in disciplines outside business and computing. In the humanities, for example, the distinction between foundation-oriented and practice-oriented assignments is less immediately intuitive, and discipline-specific adaptations may be necessary.

Third, longitudinal research is needed to track how the framework performs as AI capabilities evolve. An assignment that is appropriately classified as Tier 1 today may need reclassification if future AI models can engage with it at higher cognitive levels. Understanding how faculty update their classifications over time, and what cues prompt reclassification, would contribute to the framework's long-term viability.

Fourth, the intersection between the framework and equity concerns warrants attention. If Tier 3 assignments require access to paid AI tools (e.g., premium subscriptions to advanced models), students from lower-income backgrounds may be disadvantaged. Research should examine how institutional provision of AI tools, or the design of Tier 3 assignments around freely available tools, can mitigate this risk.

Finally, the framework could be extended to address faculty use of AI for generating course materials, providing feedback, or designing assessments. The current version focuses on student-facing AI use, but the parallel question of when and how faculty should use AI in their own pedagogical practice is equally pressing [23–25].

A Sample Syllabus Language for Each Tier

The following sample language may be adapted for use in course syllabi to communicate the Three-Tier Decision Framework to students.

Tier 1 (Restricted) Sample Statement

"For assignments labeled Tier 1, you are expected to complete all work independently and without the use of generative AI tools (e.g., ChatGPT, Copilot, Gemini). These assignments are designed to develop foundational skills essential to your success in later coursework and your career. Using AI to generate answers for these assignments constitutes an academic integrity violation. If you are unsure whether a specific use of AI is permitted, ask the instructor before submitting."

Tier 2 (Guided) Sample Statement

"For assignments labeled Tier 2, you may use generative AI tools under the following conditions: (1) you must disclose all AI interactions by submitting a prompt log as an appendix to your assignment; (2) you must critically evaluate any AI-generated content and take responsibility for its accuracy; (3) the substantial intellectual contribution, the analysis, argumentation, or creative synthesis, must be your own. AI may be used for brainstorming, grammar checking, or generating preliminary drafts, but the final submission must demonstrate your independent thinking."

Tier 3 (Open) Sample Statement

"For assignments labeled Tier 3, you are encouraged to use generative AI tools as part of the assignment. Effective use of AI is one of the learning objectives. Your grade will be based on the quality of your prompts,

your ability to evaluate and improve AI outputs, and the overall quality of the integrated final product. You must submit a complete prompt log and a reflective commentary explaining how you used AI and what you would do differently next time."

References

[1] E. Kasneci, K. Sessler, S. Küchemann, M. Bannert, D. Dementieva, F. Fischer, U. Gasser, G. Groh, S. Günnemann, E. Hüllermeier, S. Krusche, G. Kutyniok, T. Michaeli, C. Nerdel, J. Pfeffer, O. Poquet, M. Sailer, A. Schmidt, T. Seidel, M. Stadler, J. Weller, J. Kuhn, and G. Kasneci, "ChatGPT for good? on opportunities and challenges of large language models for education," *Learning and Individual Differences*, vol. 103, p. 102274, 2023.

[2] J. Rudolph, S. Tan, and S. Tan, "War of the chatbots: Bard, Bing Chat, ChatGPT, Ernie and beyond. the new AI gold rush and its impact on higher education," *Journal of Applied Learning and Teaching*, vol. 6, no. 1, pp. 364–389, 2023.

[3] E. R. Mollick and L. Mollick, "Assigning AI: Seven approaches for students, with prompts," *SSRN Electronic Journal*, 2023.

[4] M. Perkins, "Academic integrity considerations of AI large language models in the post-pandemic era: ChatGPT and beyond," *Journal of University Teaching & Learning Practice*, vol. 20, no. 2, pp. 1–24, 2023.

[5] J. Prather, P. Denny, J. Leinonen, B. A. Becker, I. Albluwi, M. Craig, H. Keuning, N. Kiesler, T. Kohn, A. Luxton-Reilly, S. MacNeil, A. Petersen, R. Pettit, B. N. Reeves, and J. Savelka, "The robots are here: Navigating the generative AI revolution in computing education," in *Proceedings of the 2023 Working Group Reports on Innovation and Technology in Computer Science Education*, pp. 108–159, 2023.

[6] D. R. E. Cotton, P. A. Cotton, and J. R. Shipway, "Chatting and cheating: Ensuring academic integrity in the era of ChatGPT," *Innovations in Education and Teaching International*, vol. 61, no. 2, pp. 228–239, 2024.

[7] R. Luckin, W. Holmes, M. Griffiths, and L. B. Forcier, "Intelligence unleashed: An argument for AI in education," tech. rep., Pearson Education, London, 2016.

[8] O. Zawacki-Richter, V. I. Marín, M. Bond, and F. Gouverneur, "Systematic review of research on artificial intelligence applications in higher education: Where are the educators?," *International Journal of Educational Technology in Higher Education*, vol. 16, no. 39, pp. 1–27, 2019.

[9] S. A. D. Popenici and S. Kerr, "Exploring the impact of artificial intelligence on teaching and learning in higher education," *Research and Practice in Technology Enhanced Learning*, vol. 12, no. 22, pp. 1–13, 2017.

[10] L. Yan, L. Sha, R. Zhao, Y. Li, R. Martinez-Maldonado, G. Chen, X. Li, Y. Jin, and D. Gašević, "Practical and ethical challenges of large language models in education: A systematic scoping review," *British Journal of Educational Technology*, vol. 55, no. 1, pp. 90–112, 2024.

[11] D. L. McCabe, L. K. Treviño, and K. D. Butterfield, "Cheating in academic institutions: A decade of research," *Ethics & Behavior*, vol. 11, no. 3, pp. 219–232, 2001.

[12] T. Bretag, R. Harper, M. Burton, C. Ellis, P. Newton, P. Rozenberg, S. Saddiqui, and K. van Haeringen, "Contract cheating: A survey of Australian university students," *Studies in Higher Education*, vol. 44, no. 11, pp. 1837–1856, 2019.

[13] B. S. Bloom, ed., *Taxonomy of Educational Objectives: The Classification of Educational Goals. Handbook I: Cognitive Domain*. New York: David McKay Company, 1956.

[14] L. W. Anderson and D. R. Krathwohl, eds., *A Taxonomy for Learning, Teaching, and Assessing: A Revision of Bloom's Taxonomy of Educational Objectives*. New York: Longman, 2001.

[15] W. M. Lim, A. Gunasekara, J. L. Pallant, J. I. Pallant, and E. Pechenkina, "Generative AI and the future of education: Ragnarök or reformation? a paradoxical perspective from management educators," *The International Journal of Management Education*, vol. 21, no. 2, p. 100790, 2023.

[16] C. Van Slyke, R. D. Johnson, and J. Sarabadani, "Generative artificial intelligence in information systems education: Challenges, consequences, and responses," *Communications of the Association for Information Systems*, vol. 53, no. 1, pp. 1–21, 2023.

[17] H. Crompton and D. Burke, "Artificial intelligence in higher education: The state of the field," *International Journal of Educational Technology in Higher Education*, vol. 20, no. 22, pp. 1–22, 2023.

[18] Y. Dai, A. Liu, and C. P. Lim, "Reconceptualizing ChatGPT and generative AI as a student-driven innovation in higher education," *Procedia CIRP*, vol. 119, pp. 84–90, 2023.

[19] M. Bearman, J. Ryan, and R. Ajjawi, "Discourses of artificial intelligence in higher education: A critical literature review," *Higher Education*, vol. 86, no. 2, pp. 369–385, 2023.

[20] J. Biggs, "Enhancing teaching through constructive alignment," *Higher Education*, vol. 32, no. 3, pp. 347–364, 1996.

[21] J. Crawford, M. Cowling, and K.-A. Allen, "Leadership is needed for ethical ChatGPT: Character, assessment, and learning using artificial intelligence (AI)," *Journal of University Teaching & Learning Practice*, vol. 20, no. 3, pp. 1–19, 2023.

[22] T. Trust, J. Whalen, and C. Mouza, "Editorial: ChatGPT: Challenges, opportunities, and implications for teacher education," *Contemporary Issues in Technology and Teacher Education*, vol. 23, no. 1, pp. 1–23, 2023.

[23] A. Tlili, B. Shehata, M. A. Adarkwah, A. Bozkurt, D. T. Hickey, R. Huang, and B. Agyemang, "What if the devil is my guardian angel: ChatGPT as a case study of using chatbots in education," *Smart Learning Environments*, vol. 10, no. 15, pp. 1–24, 2023.

[24] N. Selwyn, *Should Robots Replace Teachers? AI and the Future of Education*. Cambridge: Polity Press, 2019.

[25] X. Zhai, X. Chu, C. S. Chai, M. S. Y. Jong, A. Istenic, J. M. Spector, J.-B. Liu, J. Yuan, and Y. Li, "A review of artificial intelligence (AI) in education from 2010 to 2020," *Complexity*, vol. 2021, p. 8812542, 2021.