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From Curiosity to Competence: A Framework for Responsible Generative AI Use in Education

Tarun U[1] and Dr Kiran Kumar M N[2]

[1] *3rd Year BCA Student, BMS College of Commerce and Management, Bengaluru*
[2] *Head of Department, Department of Computer Applications, BMS College of Commerce and Management, Bengaluru*
Corresponding author email: tarunumesh85@gmail.com

Abstract - Generative Artificial Intelligence (GenAI) tools such as large language models are rapidly reshaping how students learn, faculty teach, and institutions assess performance. This conceptual paper examines how learners can move from early curiosity about GenAI to competent, responsible use, and how institutions can support that progression while protecting learning outcomes, academic integrity, and employability skills. Drawing on a narrative review of selected literature on GenAI in higher education, academic integrity, AI literacy, and technology acceptance, the paper identifies a gap: adoption, integrity, and assessment are rarely treated together. It extends the Technology Acceptance Model, using perceived usefulness, ease of use, and trust, with perceived time savings and concerns about accuracy, over-reliance, and plagiarism, to develop testable propositions about what drives and sustains GenAI use. The paper then proposes a Responsible GenAI Integration Framework with four pillars: transparent usage policies, AI literacy training, redesigned assessments, and human-in-the-loop verification of AI-generated outputs. These pillars are linked to four stages of learner progression, from curiosity to competence. A research agenda outlines how the propositions and framework can be validated through student surveys and faculty interviews. The paper contributes to the literature on Human–AI collaboration in education by offering a structured, theory-informed model for educators, institutional leaders, and policymakers who wish to harness GenAI's benefits while safeguarding critical thinking and ethical academic practice.

Keywords: Generative AI, Responsible AI, Higher Education, Academic Integrity, Human–AI Collaboration

1. INTRODUCTION

Since the public release of conversational large language models (LLMs) in late 2022, Generative Artificial Intelligence has moved from a research topic to an everyday study tool.

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Students use it to explain concepts, draft and debug code, summarise readings, and structure assignments. Faculty, in turn, face questions that existing academic frameworks were not designed to answer: what counts as legitimate assistance, how authorship should be judged, and which skills a graduate must still demonstrate without a machine at hand. Early scholarship describes both sides of this tension, pointing to personalised support and efficiency on one hand and to risks of inaccuracy, bias, and weakened independent thinking on the other (Kasneci et al., 2023; Zawacki-Richter et al., 2019).

Much of the discussion so far is either normative (what institutions *should* do) or technology-centred (what the tools *can* do). Less attention has been paid to the learner's journey: how a student progresses from first curiosity, through experimentation, to a stage where use is deliberate, verified, and ethically defensible. This paper treats that progression, from curiosity to competence, as its central object. In the Indian higher education context, where the National Education Policy 2020 emphasises technology-enabled and skills-oriented learning (Ministry of Education, 2020), the question of how to build competent rather than merely frequent use is especially pressing.

Three gaps motivate the paper. First, adoption research often asks *whether* students use GenAI but less often *what sustains or discourages* continued use. Second, adoption, academic integrity, and assessment are usually discussed in separate literatures, which hides how they interact. Third, many recommendations are lists of good practice without a structure that connects policy, literacy, assessment, and verification into one coherent model. The paper aligns with Theme 1 of CONFLUENCE-2026 (AI, Data and Intelligent Systems), in particular the sub-themes *Artificial Intelligence and Generative AI*, *AI Applications in Business, Education and Society*, and *Human–AI Collaboration*.

The paper makes three contributions: (i) it extends the Technology Acceptance Model for the GenAI context and states five testable propositions; (ii) it defines four stages of learner progression from curiosity to competence; and (iii) it proposes a four-pillar Responsible GenAI Integration Framework, together with an assessment-redesign guide and a research agenda for empirical validation. The paper is conceptual: it does not report new survey or interview data, and its propositions are presented as hypotheses to be tested, not as established findings.

2. SCOPE AND APPROACH OF THE REVIEW

The paper follows a narrative review approach. Sources were selected for relevance to four strands: GenAI and large language models in education, academic integrity and assessment, AI

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literacy and Human–AI collaboration, and technology acceptance theory. They include peer-reviewed journal articles, a conference paper, foundational theory texts, and policy documents from UNESCO, the Government of India, and an Australian higher-education regulator. The review is purposive rather than exhaustive: it was not a systematic review with a pre-registered protocol, and this limits the claims that can be made (see Section 9). The selected literature was used to (a) establish what is known, (b) identify the gap described in Section 1, and (c) ground the propositions and framework in prior work.

3. LITERATURE REVIEW AND THEORETICAL BACKGROUND

3.1 Generative AI in higher education

A systematic review of AI in higher education found research concentrated on applications such as profiling, assessment, and intelligent tutoring, with limited engagement with pedagogical theory and few educators among the authors (Zawacki-Richter et al., 2019). Generative models change this balance because they interact with learners directly in natural language. Kasneci et al. (2023) outline opportunities such as adaptive explanations, feedback generation, and support for teachers' preparation, while warning that students may over-rely on outputs, that responses can be incorrect while sounding plausible, and that educators need new competencies to use such tools well. UNESCO (2023) similarly calls for a human-centred approach, with safeguards for data privacy and age-appropriate use, and capacity building for teachers.

3.2 Academic integrity and assessment

A second strand concerns integrity. Cotton, Cotton and Shipway (2024) discuss how LLM-generated text challenges academic integrity and recommend a combination of measures, including clear policy, student education, and assessment design, rather than any single safeguard. Sullivan, Kelly and McLaughlin (2023) examine early institutional and media responses to ChatGPT, highlighting integrity concerns alongside potential learning benefits. Lodge et al. (2023) argue that assessment must both prepare students to engage ethically with AI and remain a trustworthy record of what students have learned. These works motivate the policy and assessment pillars of the framework in Section 6.

3.3 Technology Acceptance Model

The Technology Acceptance Model (TAM) explains technology use through two beliefs: perceived usefulness (the degree to which a person believes the technology improves performance) and perceived ease of use (the degree to which it is free of effort) (Davis, 1989).

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Extensions such as TAM2 and UTAUT add social influence, facilitating conditions, and related constructs (Venkatesh & Davis, 2000; Venkatesh et al., 2003). For GenAI, trust is a natural addition: because outputs may be wrong, a learner's willingness to rely on them depends on perceived reliability. The model developed in Section 4 therefore keeps perceived usefulness, ease of use, and trust as core constructs and adds perceived time savings and concern as context-specific variables.

3.4 AI literacy and Human–AI collaboration

Long and Magerko (2020) define AI literacy as a set of competencies that enable people to evaluate AI technologies critically, communicate and collaborate with AI, and use it as a tool. This definition fits the progression studied here: competence is not frequency of use but the ability to judge when to use a tool, how to prompt it, how to verify what it returns, and when to set it aside. Human–AI collaboration, in this sense, keeps the human accountable for the final output, a principle that underlies the human-in-the-loop pillar of the framework.

3.5 Research gap

The literature offers adoption models, integrity concerns, and literacy definitions, but rarely joins them. No single model, to the authors' knowledge from the sources reviewed, links the drivers of student use, the stages by which competence develops, and the institutional measures that support both. This paper proposes such a model.

4. CONCEPTUAL MODEL AND PROPOSITIONS

Figure 1 presents the extended TAM for GenAI use. Usage intensity (how extensively and how consistently a learner uses GenAI) is the outcome. Four beliefs are expected to drive it: perceived usefulness, perceived ease of use, trust in outputs, and perceived time savings. Concern about accuracy, over-reliance, and plagiarism is expected to moderate the link between usefulness and sustained use. Table 1 states the resulting propositions with their grounding.

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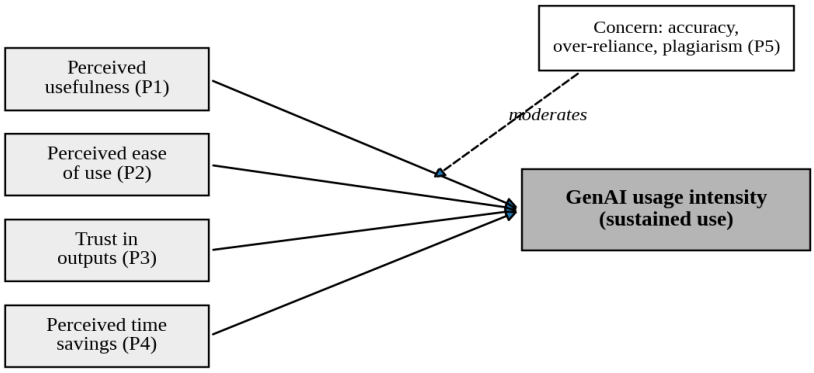


Figure 1: Extended Technology Acceptance Model for GenAI use (conceptual; to be tested)

Table 1: Propositions of the extended model

No.	Proposition	Rationale	Anchoring sources
P1	Perceived usefulness positively influences GenAI usage intensity.	Usefulness is the core predictor of technology use in TAM.	Davis (1989); Venkatesh & Davis (2000)
P2	Perceived ease of use positively influences usage intensity, though its distinguishing power may be weak because natural-language interfaces are easy for most users.	Ease of use influences usage mainly through usefulness; GenAI lowers the effort barrier for most users.	Davis (1989); Kasneci et al. (2023)
P3	Trust in the reliability of outputs positively influences usage intensity.	Outputs can be incorrect yet fluent, so reliance depends on perceived reliability.	Kasneci et al. (2023)
P4	Perceived time savings positively influence usage intensity.	Efficiency gains are a central reported benefit and a practical form of perceived usefulness.	Kasneci et al. (2023); Davis (1989)
P5	Concern about accuracy, over-reliance, and plagiarism weakens the effect of perceived usefulness on sustained use.	Integrity and reliability worries shape whether early use continues.	Cotton et al. (2024); Sullivan et al. (2023)

Source: Developed by the authors. Propositions are hypotheses for future testing, not findings.

5. STAGES OF LEARNER PROGRESSION

Drawing on the AI literacy competencies described by Long and Magerko (2020), the paper distinguishes four stages through which a learner is expected to pass. The stages are heuristic and a learner can move between them depending on the task.

- **Curiosity.** The learner experiments with GenAI without rules or a method, and has little ability to judge output quality.
- **Guided exploration.** The learner uses GenAI within stated boundaries, such as course-level rules on permitted use, and begins to compare outputs with course material.

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- **Informed use.** The learner verifies outputs against reliable sources, discloses assistance, and understands typical failure modes such as fabricated references and bias.
- **Competence.** The learner decides independently when GenAI is appropriate, uses it to extend rather than replace their own reasoning, and remains accountable for the final work.

The main implication is that frequent use does not indicate competence. A student can be a heavy user at the curiosity stage; the stages are defined by the quality of judgement, not by usage volume.

6. PROPOSED FRAMEWORK: RESPONSIBLE GENAI INTEGRATION

The framework rests on four institutional pillars that together move learners through the stages above while keeping humans accountable for outcomes (Figure 2 and Table 3). The pillars are derived from the literature reviewed in Section 3 and are a proposed model; they have not yet been empirically validated.

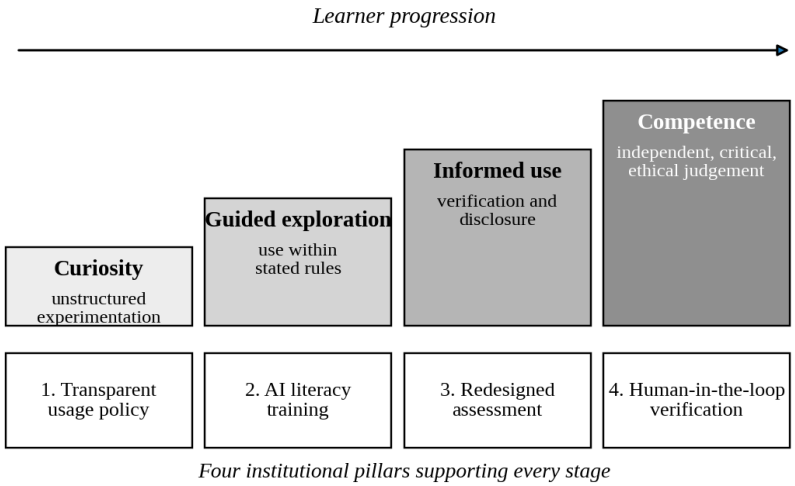


Figure 2: The Responsible GenAI Integration Framework: learner stages supported by four institutional pillars

6.1 Pillar 1: Transparent usage policy

Institutions state in writing which uses of GenAI are permitted, restricted, or prohibited, at institution and course level, and require disclosure of AI assistance in submitted work. Explicit expectations remove ambiguity that otherwise leaves each student to guess, and they give faculty a consistent basis for judging misconduct. This responds to calls for clear policy as part of a combined integrity strategy (Cotton et al., 2024; UNESCO, 2023).

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6.2 Pillar 2: AI literacy training

Short modules for students and faculty cover how LLMs work and fail, effective prompting, bias, data privacy, and how to acknowledge AI assistance. Following Long and Magerko (2020), the aim is the ability to evaluate, collaborate with, and use AI critically, not tool operation alone. Faculty training is included because educators themselves need new competencies (Kasneci et al., 2023).

6.3 Pillar 3: Redesigned assessment

Assessment is redesigned so that it both prepares students to use AI ethically and remains a trustworthy record of learning (Lodge et al., 2023). Practical measures include evidence of process, oral or live demonstration, applied tasks tied to local or recent context, and clear labelling of which tasks permit AI and which do not. Table 2 gives illustrative redesigns for common assignment types, including programming tasks relevant to computer applications programmes.

Table 2: Illustrative assessment redesigns (examples proposed by the authors)

Traditional task	AI-resilient redesign	Skill evidenced
Take-home essay	Draft history plus short reflection on how AI was used, followed by a brief viva	Reasoning, authorship, disclosure
Programming assignment	Supervised lab component plus walkthrough in which the student explains their code and fixes a seeded bug	Understanding, debugging, accountability
Case analysis	In-class analysis of a case issued on the day, with AI-permitted and AI-free parts labelled	Applied judgement
Literature summary	Students critique an AI-generated summary and identify errors against the sources	Verification, critical evaluation

Source: Developed by the authors; not yet tested in practice.

6.4 Pillar 4: Human-in-the-loop verification

Students verify AI output against reliable sources, record what was checked, and remain accountable for the final submission; faculty periodically review samples of work and the verification records. This pillar operationalises the Human–AI collaboration principle that AI assists while the human decides and answers for the result (Long & Magerko, 2020).

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Table 3: Summary of the four pillars

Pillar	Core actions	Primary owner	Gap addressed
1. Transparent usage policy	Written institution- and course-level rules; disclosure of AI assistance; clear consequences	Institutional leaders, academic council	Unclear guidelines; inconsistent expectations
2. AI literacy training	Modules on how LLMs work and fail, prompting, bias, privacy, and acknowledging AI use	Faculty development cell, IT and library teams	Over-reliance; uneven readiness
3. Redesigned assessment	Process evidence, oral or live tasks, contextual problems, labelled AI-permitted and AI-free tasks	Faculty, programme coordinators	Plagiarism; inconsistent assessment
4. Human-in-the-loop verification	Student verification records; accountability for final work; faculty sampling	Students and faculty jointly	Accuracy concerns; erosion of critical thinking

Source: Developed by the authors from the literature reviewed.

6.5 Interdependence and phased implementation

The pillars are interdependent. A policy without literacy training is hard to follow; training without redesigned assessment leaves incentives unchanged; and assessment reform without a verification habit may still produce unchecked reliance. Institutions can implement the pillars in phases: begin with a simple disclosure policy and a short literacy module, then redesign assessments course by course, and finally embed verification records and periodic review. Policies should be reviewed regularly because the tools change quickly.

7. IMPLICATIONS

For educators: state expectations for each assessment explicitly, teach verification as a graded skill, and design tasks that reward reasoning and process. **For institutional leaders:** adopt a written, regularly reviewed GenAI policy and invest in joint student–faculty literacy training rather than relying on detection tools alone. **For policymakers:** provide common baseline guidance, consistent with national education policy and UNESCO (2023), that institutions can adapt to their own disciplines. **For researchers:** the propositions and framework supply testable claims, for example that institutions adopting all four pillars will show better calibrated trust and fewer integrity incidents than those adopting none.

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8. RESEARCH AGENDA FOR VALIDATION

Empirical validation is the natural next step. A convergent mixed-methods design is proposed. **Student survey:** a questionnaire measuring perceived usefulness, ease of use, trust, time savings, concern, and usage intensity on five-point Likert scales adapted from Davis (1989), tested with multiple linear regression and a usefulness × concern interaction term for P5, with reliability assessed by Cronbach's alpha (Nunnally & Bernstein, 1994) and regression assumptions checked following Hair et al. (2019). **Faculty interviews:** semi-structured interviews on personal use, attitudes to student use, institutional policy, and assessment practice, analysed using thematic analysis (Braun & Clarke, 2006). **Pilot implementation:** a design-based pilot of the four pillars in selected courses, comparing integrity incidents, student verification behaviour, and assessment quality before and after. Longitudinal designs could further track movement across the four stages, and the model could be extended with social influence and facilitating conditions (Venkatesh et al., 2003). Studies should obtain informed consent, protect anonymity, and secure institutional ethics approval where required.

9. LIMITATIONS

The paper has several limitations. It is conceptual and reports no primary data, so the propositions and framework remain untested. The review is narrative and purposive, not systematic, so relevant studies may have been missed and the selection may reflect the authors' judgement. The field is moving quickly, and sources reviewed may be overtaken by newer evidence. The assessment examples in Table 3 are illustrative and have not been piloted. Finally, the framework is generic and will need adaptation to specific disciplines, institutional resources, and regulatory contexts.

10. CONCLUSION

This paper examined how learners can move from curiosity about GenAI to competent, responsible use. It extended the Technology Acceptance Model with trust, time savings, and concern to state five testable propositions, defined four stages of learner progression, and proposed a four-pillar framework of transparent policy, AI literacy training, redesigned assessment, and human-in-the-loop verification. The central message is that responsible use is built, not assumed: institutions that make expectations explicit, teach verification, and assess authentic performance are better placed to gain the benefits of GenAI while protecting critical thinking and academic integrity. The proposed research agenda offers a route to test and refine these ideas empirically.

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