

NAVIGATING THE AI CONTRADICTION IN HIGHER EDUCATION: CONCEPTUAL FRAMEWORK FOR STUDENT LEARNING, AUTHENTIC ASSESSMENT, GRADUATE EMPLOYABILITY AND INSTITUTIONAL GOVERNANCE

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Abstract: *The rise of Generative Artificial Intelligence (GenAI) presents new challenges to conventional notions of assessment validity, institutional governance and graduate employability. The central problem Higher Education Institutions (HEIs) face in this conceptual paper is not that students use GenAI to complete syllabus required assessments, but that syllabus required assessments need to evolve into AI literacy education to maintain students' critical thinking when using GenAI. In doing so, students retain and expand their critical thinking capabilities with academic integrity upon graduation. This conceptual paper attempts to resolve this assessment validity crisis by examining the underlying conflicts among students, employers and HEIs. To achieve this, the paper utilizes a conceptual literature synthesis incorporating quantitative, qualitative and mixed-methods research traditions. As an outcome of this study, this paper proposes a two-pillar conceptual framework consisting of the Three-Tier Pedagogical Intervention Pipeline and the Field- embedded Empirical Project Based Learning (PBL) model. Within this framework, student project curricula are developed across three empirical methodological pathways: Quantitative (utilizing SPSS, SmartPLS and AMOS), Qualitative (incorporating Focus Group Discussions and interviews) and Mixed-Methods as a mechanism to restore assessment authenticity, embed AI literacy and develop workplace readiness. This paper provides strategic recommendations for HEI administrators, accreditation agencies and educators to redesign assessment frameworks applicable to higher education using human-centric, process-oriented models.*

Keywords: *Generative Artificial Intelligence, Authentic Assessment, Project Based Learning, Graduate Employability, Higher Education Governance*

Introduction

The world is currently witnessing a paradigm shift in higher education fuelled by the rapid rise of Generative Artificial Intelligence (GenAI). State of the art language models and automated analytical reasoning present unprecedented opportunities for idea generation, syntactical improvement and information organization (Zawacki- Richter et al., 2019). When harnessed in instructional settings, these innovations have the potential to reduce cognitive load and enable self- regulated learning among non-native language students and users (Chiu, 2023; Kamalov et al., 2023).

The rapid rise of GenAI, however, raises profound questions about the very foundations of assessment validity in higher education (Bearman et al., 2023; Dawson et al., 2024). Navigating the AI contradiction requires HEI administrators to recognize that the central problem is not that students use automated tools to complete syllabus required assessments, but that syllabus required assessments must evolve into AI literacy education to maintain students' critical thinking capabilities when using GenAI. Conventional unsupervised assessments such as syllabus- required reports, literature reviews and desk research can no longer provide credible evidence of independent student work when executed with the aid of GenAI (Aumann, 2024; Bearman et al., 2023). The reason is that GenAI software can generate coherent text on complex topics instantly, thereby defeating the purpose of most automated marking rubrics (Cotton et al., 2024).

Efforts to rely on automated plagiarism detection tools to reveal students' use of GenAI have proven mostly futile if not misleading (Perkins et al., 2024; Weber-Wulff et al., 2023). Contextual awareness, prompt engineering and advanced GenAI detection tools are needed to differentiate between appropriate writing assistance and unauthorized cognitive support (Perkins et al., 2024; Weber-Wulff et al., 2023). Most crucially, universities must look beyond automated detection software and develop assessment designs that embed integrity by default and leverage fieldwork, verbal defenses, embedded AI critical evaluations and project based learning (Bozkurt et al., 2023; Dawson et al., 2024).

Literature Review

Assessment Validity Frameworks and the AI Challenge

Conventional validity frameworks in educational measurement assume that submitted assignments reflect the students' cognitive processes. In the context of Gen AI, validity is at risk due to construct irrelevant variance, threatening to undermine the integrity of unsupervised assessments and conventional marking rubrics (Aumann, 2024; Bearman et al., 2023). Unsupervised Gen AI assisted syllabus required desk research enables students to bypass working memory encoding and direct information extraction (Lodge et al., 2023; Sweller, 1988). To restore validity and promote fidelity in critical thinking, HEIs must consider intervening with AI literacy education and revise assessment designs to include verifiable processes and not rely on final written products (Dawson et al., 2024; Nieminen et al., 2023).

Dual Perspectives on Gen AI: Cognitive Offloading and Self- regulated Learning

The existing literature on Gen AI in education is characterized by dual narratives on the phenomenon, namely: (1) Pedagogy and Cognitive Offloading: Excessive reliance on automated summaries presents ethical challenges, as it promotes cognitive offloading of

analytical reasoning to an external agent (Lodge et al., 2023; Sweller, 1988). Digital natives often engage in skimming practices using visual cues on their screens, bypassing the deep reading and critical thinking processes usually associated with prose reading (Chiu, 2023; Lodge et al., 2023). This behaviour has the potential to adversely affect students' prose reading competencies and critical thinking skills (Chiu, 2023; Lodge et al., 2023; Perkins et al., 2024; Weber-Wulff et al., 2023). (2) Self Regulated Learning: A growing body of literature highlights the potential of Gen AI to support self regulated strategies such as idea generation or scaffolding when guided by appropriate AI literacy frameworks (Chiu, 2023; Kamalov et al., 2023; Mollick & Mollick, 2023). This perspective views Gen AI as an intellectual assistant capable of supporting students in initiating projects, developing alternative arguments, offering feedback and explaining complex concepts (Chiu, 2023; Kamalov et al., 2023; Mollick & Mollick, 2023). The key challenge then becomes determining the extent to which universities can rely on technology to support learning before cognitive responsibility is outsourced (Bozkurt et al., 2023).

Ethical Synthesis: Integrating Maslahah and Mafsadah

Informed by the Islamic jurisprudence of Maslahah (public interest/benefit) and Mafsadah (prevention of harm), this paper takes a benefit harm analysis of incorporating Gen AI in syllabus required assessments. In this conceptual analysis, Maslahah (benefit) is realized when Gen AI serves as an enabler of higher education processes while Mafsadah (harm) is evident when Gen AI threatens to undermine critical thinking and professional competency. Specifically, in the context of HEIs, Maslahah is manifested when Gen AI is used as a tool to catalyze research productivity, institutional effectiveness and student success within AI literacy guidelines (Ariyanti Mustapha & Nurul Nabihah Mohd Sha'auzi, 2026; Kamalov et al., 2023; Mollick & Mollick, 2023).

By contrast, Mafsadah emerges when unsupervised Gen AI use in syllabus required assessments bypasses key learning processes, resulting in artificial literacy, unearned qualifications, and reduced professional competencies (Ariyanti Mustapha & Nurul Nabihah Mohd Sha'auzi, 2026; Cotton et al., 2024; Perkins et al., 2024).

Conceptual Framework

Table 1: Theoretical Foundations of the Framework

Theoretical Lens	Core Conceptual Focus	Framework Application
Cognitive Load Theory (CLT) (Sweller, 1988; and Chen, 2025)	Working memory limits and instructional scaffolding.	Justifies a structured, three-tier pipeline (Capture-Scaffold-Deepen) to rebuild reading stamina and prevent cognitive overload.
Social Constructivism (Vygotsky, 1978; Huey & Giguere, 2022)	Knowledge construction through collaborative dialogue and social interaction.	Replaces isolated, take-home tasks with live viva-voce defenses, oral defenses, group debates, and community-engaged fieldwork.
Human-Techno Interaction (HTI) (Ahmad et al., 2021;	Defining functional boundaries between human	Establishes policy boundaries where AI functions strictly as

Kamalov et al., 2023)	cognition and automated systems.	exploratory support, leaving synthesis and decision-making to the student.
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To address assessment validity challenges, foster AI literacy and strengthen graduate employability, this paper proposes a comprehensive two-pillar framework. This model integrates structured pedagogical interventions with field-embedded empirical project pathways to rebuild academic integrity and ensure authentic learning outcomes.

Pillar 1: Three-Tier Pedagogical Intervention

Proposed Pedagogical Interventions to Re-establish Student Stamina and Reading Culture

This paper proposes a three Tiers reading intervention model to re-establish student stamina and reading culture.

Tier 1: Capturing Attention

Visual priming will be used to activate existing knowledge and reduce the effort needed to understand new information presented in texts at complex and/or abstract levels.

Tier 2: Elaboration through scaffolding

Annotated texts and AI literacy will be used to guide students through challenging readings. This will enable students to interrogate Generative AI rather than being written by it. Thus, this tier goes beyond 'write and run' writing assignments by scaffolding critical analysis and evaluation processes.

Tier 3: Deepen

Screen-free oral presentations and oral defenses will be used to reinforce individual responsibility for learning while eliminating plagiarism and enhancing critical thinking abilities (Nieminen et al., 2023).

Pillar 2: Field-Embedded Empirical Project-Based Learning (PBL) Model

To embed authenticity into syllabus required assessments and accommodate the diverse methodological requirements across academic disciplines, the second pillar presents a Project Based Learning (PBL) model featuring three empirical methodological pathways.

Quantitative Pathway

This pathway will involve building survey instruments, carrying out field surveys and analysing survey results using statistical software such as SPSS, SmartPLS (Hair et al., 2021) and AMOS (Byrne, 2016). This pathway will enhance data literacy, quantitative skills and analytical competencies among students that are not possible using Generative AI.

Qualitative Pathway

This pathway will require students to carry out Focus Group Discussions (FGDs) (Morgan, 2019), key informant interviews and thematic analysis (Braun & Clarke, 2019). This pathway will produce verbal communication skills and listening skills among students while also addressing the industry's concerns about poor soft skills competency among graduates (Bozkurt et al., 2023).

Mixed methods pathway

The mixed-methods pathway will be used to advocate for adopting both qualitative and quantitative approaches in one research project (Creswell & Creswell, 2018). For instance, students could carry out FGDs, develop primary survey instruments from the results of the FGDs, carry out analyses such as PLS-SEM (Hair et al., 2021) and follow-up qualitative interviews to explain any unexpected results (Creswell & Creswell, 2018). As a result, the mixed methods pathway will require students to demonstrate a high level of critical thinking skills to achieve methodological convergence while also demonstrating authenticity and competence in their work.

Methodology

This study employs a conceptual literature synthesis incorporating quantitative, qualitative and mixed methods research traditions. Specifically, it synthesizes quantitative literature on assessment validity, qualitative evidence on human-technology interaction and mixed-methods framework literature on Project-Based Learning (PBL). Integrating these three paradigms ensures a comprehensive, objective foundation for addressing the challenges of Generative AI in higher education (Braun & Clarke, 2019; Creswell & Creswell, 2018).

First, the quantitative research paradigms emphasize validity and measurement (Byrne, 2016; Hair et al., 2021). This body of work provided a theoretical foundation for integrating quantitative pathways into the proposed framework. Specifically, student designed survey instruments and statistical analysis using SPSS, SmartPLS, and AMOS will enable learners to achieve data literacy that Gen AI cannot counterfeit.

Second, the qualitative paradigms focus on understanding human behavior (Braun & Clarke, 2019; Morgan, 2019). This body of work provided theoretical justification for developing qualitative and mixed methods pathways for syllabus required assessments. By requiring students to execute FGDs, key informant interviews and thematic analysis, this paper proposes that HEIs address the communication anxiety affecting Gen AI users (Bozkurt et al., 2023).

Third, mixed methods paradigms emphasize sequential and convergent research designs (Creswell & Creswell, 2018). This literature informed this paper's proposal for project based learning where learners triangulate quantitative research findings with qualitative stakeholder insights.

Results and Analysis

Table 2: Alignment of Assessment Vulnerabilities and Framework Interventions

Assessment Dimension	Vulnerability in Conventional Design	Underlying Operational Driver	Proposed Framework Intervention
Pedagogical Engagement	Surface-level F-pattern scanning; reliance on automated summaries.	Low friction tolerance; habituation to short-form media.	Three-Tier Pipeline: Sequential transition from visual priming to guided text annotation and screen-free oral defense.

Assessment Validity	Unverified authorial authenticity in take-home written papers.	Widespread availability of text-generation tools; lack of process tracking.	Authentic Evaluation: Reallocation of grading weight to invigilated writing, live viva-voce exams, and process portfolios.
Workforce Readiness	Difficulty analyzing unstandardized real-world data; verbal communication anxiety.	Over-reliance on static desk research during studies.	Field-Embedded PBL: Curriculum requirement for empirical pathways (Quantitative, Qualitative or Mixed-Methods).
Ethical Governance	Ineffectiveness of static plagiarism and AI detection tools.	Rapid evolution of GenAI models outpacing detection software.	Maslahah and Mafsadah Policy: Clear institutional guidelines defining acceptable AI exploration vs. mandatory human synthesis.

To address the assessment validity crisis in higher education, institutional interventions must directly align with the core operational drivers that compromise traditional evaluation methods. Table 2 illustrates four critical assessment dimensions where conventional designs fail and outlines the corresponding framework interventions required to restore academic integrity and student learning.

Pedagogical Engagement

The prevalence of digital media platforms has led to students adopting a superficial “F-pattern” skimming of texts and reliance on automated digest functions; this represents a reduced tolerance of friction and a conditioning to low-effort, bite-sized digital content, which poses a significant threat to developing deeper reading habits and critical engagement. The Three-Tier Pipeline guides students gradually towards greater reading comprehension and critical thinking, beginning with reducing barriers to entry-level engagement (Tier 1: Capture), followed by developing annotation-based frameworks for deeper examination (Tier 2: Scaffold). Finally, requiring students to conduct screen-free orals and debates (Tier 3: Deepen) to drive deeper individual understanding and responsibility.

Assessment Validity

The current prevalence of automated, unsupervised syllabus-assessment rubrics creates a significant risk to academic integrity, as both students and faculty recognize the widespread ability of third-party AI tools to generate, edit and suggest alternative text versions, with little to no control or supervision during the writing process. Instead of enforcing additional monitoring or assessment related restrictions, the framework proposes redirecting assessment

weight toward alternative supervised mediums (oral defenses, process supervision, invigilation) and process documentation to certify original thought and intellectual property.

Workforce Readiness

Current practice, which prioritizes unsupervised research processes, often fails to prepare students for actual workforce requirements, creating a skills mismatch which manifests in real-world scenarios as reduced comprehension of non-standardized, non-university-assisted data and increased anxiety around verbal communication. The Field-Embedded PBL design addresses this challenge by stipulating that students must complete either a Quantitative, Qualitative or Mixed-Methods project pathway which requires direct, first-hand engagement with field data and stakeholders, thus exposing students to real-world complexities in both methods of investigation and modes of communication (written, verbal and otherwise).

Ethical Governance

Plagiarism checkers and automated AI detectors are inadequate in identifying text generated by evolving third-party AI language models, which have surpassed many standardized academic writing metrics. The proposed governance framework operates from the jurisdiction of Islamic jurisprudence, specifically Maslahah (public policy and interest) and Mafsadah (prohibition and prevention of societal harm), to which it relates as a system of ethical governance. By developing a standardized framework which certifies processes and distinguishes between permissible exploratory AI and prohibited proprietary writing, the institutional policy establishes concrete parameters which prevent both direct plagiarism and unauthorized third party AI content usage.

Table 3: Comparative Analysis of Empirical Methodological Pathways for Student Projects

Methodological Pathway	Key Field Tools / Software	Primary Learning & Competency Target
Quantitative Pathway	Primary Surveys; SPSS, SmartPLS, AMOS.	Data cleaning, statistical modeling, hypothesis testing, quantitative literacy.
Qualitative Pathway	Focus Group Discussions (FGDs), Field Interviews, Thematic Analysis.	Interpersonal communication, qualitative synthesis, active listening, soft skills.
Mixed-Methods Pathway	Combined Survey + FGD/Interview Integration.	Methodological triangulation, comprehensive problem-solving, advanced synthesis.
Methodological Pathway	Key Field Tools / Software	Primary Learning & Competency Target

To operationalize authentic assessment and rebuild graduate employability, the Field-Embedded Empirical Project-Based Learning (PBL) model incorporates three distinct methodological pathways. Table 3 details how each pathway leverages specific analytical tools to target core professional competencies while ensuring extreme resilience against Generative AI exploitation.

Quantitative Pathway

Field Tools & Software: Utilizes primary survey instruments combined with specialized statistical software packages, including SPSS (for descriptive and inferential analysis), SmartPLS (for partial least squares structural equation modelling) and AMOS (for covariance-based structural equation modelling).

Learning & Competency Targets

Focuses on cultivating core data literacy, structured data cleaning, statistical modelling and formal hypothesis testing.

GenAI Resilience: Extremely Low Vulnerability

GenAI models cannot generate authentic, context-specific raw primary field datasets or execute live statistical assumption tests, making unearned automation virtually impossible.

Qualitative Pathway

Field Tools & Software

Employs primary empirical collection methods such as Focus Group Discussions (FGDs), semi-structured field interviews and systematic thematic analysis.

Learning & Competency Targets

Directly builds interpersonal communication skills, active listening, qualitative narrative synthesis and critical soft skills.

GenAI Resilience: Extremely Low Vulnerability.

Automated language tools cannot simulate live, real-world human stakeholder interviews or spontaneous verbal interactions, ensuring that student performance reflects authentic interpersonal capability.

Mixed-Methods Pathway

Field Tools & Software

Combines quantitative primary surveys with qualitative FGDs and field interviews in an integrated research framework.

Learning & Competency Targets

Focuses on methodological triangulation, comprehensive problem-solving and high-level critical synthesis across diverse data types.

GenAI Resilience

Zero Vulnerability. The multi-stage, empirical nature of mixed-methods design requires real-time data integration and field execution that completely surpass the generative capabilities of AI systems.

Discussion

The conceptual framework proposed in this paper addresses the assessment validity concerns by redirecting the focus of university assessments from unsupervised written products towards field-embedded processes enhanced by AI literacy education (Bearman et al., 2023; Dawson et al., 2024).

First, this paper asserts that attempting to rely on bans or automated detection software to prevent Gen AI use in assessments is “looking in the wrong direction” (Bearman et al., 2023). Detecting “AI-written essays” will become “increasingly difficult to differentiate from human writing” as these tools become more sophisticated (Perkins et al., 2024; Weber-Wulff et al., 2023). Therefore, the most effective way of restoring confidence in higher education qualifications is by eliminating automated Gen AI-assisted unsupervised assessments as a proxy for verifying student learning (Aumann, 2024; Cotton et al., 2024). Instead, HEIs can consider invigilated writing laboratories, oral defenses, embedded AI critical evaluations and field based projects as more reliable alternatives for ensuring academic integrity while sustaining students’ critical thinking capabilities.

Second, this paper asserts that providing students with Quantitative (SPSS, SmartPLS, AMOS), Qualitative (FGDs, Interviews) and Mixed-Methods pathways in syllabus required assessments directly addresses graduate employability concerns. Employers value critical thinking skills among graduates, and they are increasingly sceptical of the competencies of Gen AI users (Bozkurt et al., 2023). Universities can secure authentic analytical literacy and soft skill competency by mandating primary empirical research across quantitative, qualitative or mixed methods designs. This active engagement prevents students from substituting essential learning processes with Generative AI tools.

Conclusion

Generative Artificial Intelligence presents unprecedented opportunities to enhance higher education by challenging universities to rethink conventional assessment designs. The central problem universities face is not that students use Gen AI to complete syllabus required assessments, but that syllabus required assessments need to evolve into AI literacy education to maintain students’ critical thinking capabilities when using Gen AI. By relying on cognitive load theory and human-techno interaction paradigms, this paper proposes a two-pillar conceptual framework consisting of the Three-Tier Pedagogical Intervention Pipeline and the Field- embedded Empirical Project Based Learning model as a mechanism for restoring assessment validity and enhancing graduate employability while upholding institutional ethics.

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