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AI as Co-Designer and Feedback Partner: Enhancing Human Judgment

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Abstract: Artificial intelligence (AI) is shaping the future of higher education, tasking educators with transforming teaching, learning, and assessment practices to consider how AI can enhance the educational environment. With its increasing availability, it is important for administrators, faculty, and students to explore the practical nature of AI use prior to entry into the workforce. Faculty must also reevaluate how they approach assessing student learning, tasking them to rethink each assessment's purpose, how it will inform future practice, and how it will prepare learners to use AI. Furthermore, faculty must also be prepared to consider the collaborative nature of AI, transforming their mindset to consider AI as an active co-designer and partner, one that does not seek to diminish the educator's human judgment. This manuscript will articulate the importance of co-design, where AI and educators collaboratively shape assessment tools, and serve to champion feedback partnerships that enhance reflective practice for both students and faculty.

Keywords: *artificial intelligence, assessment, co-designer, feedback partner, higher education human judgment*

Introduction

The rapid evolution of artificial intelligence (AI) in higher education is transforming assessment practices, presenting both profound opportunities and critical responsibilities for educators, researchers, and administrators. With the increasing availability and utilization of AI, faculty are struggling to determine if work submitted is that of the student's own genuine intellectual ability or produced by freely available AI sources. Essentially, the integration of AI is challenging faculty to reevaluate how they approach assessing student learning, tasking them with rethinking each assessment's purpose, the included content and format of the assessment, and its overall design (Liang et al., 2025).

As authors who have navigated the changing landscape of digital pedagogy, we will reflect on personal as well as documented experiences integrating AI tools into assessment design and feedback processes. AI is no longer a distant concept, but an active co-designer, collaborating with educators to create adaptive, personalized, and inclusive assessment strategies (Liang et al., 2025). Through iterative engagement, AI systems support formative feedback cycles, offering students timely insights and fostering deeper learning. This partnership, however, does not diminish the irreplaceable role of

human judgment (Raskob et al., 2025). Our journey reveals that the wisdom, empathy, and contextual understanding educators bring to assessment remain essential, especially in interpreting nuanced student responses and navigating ethical complexities.

Augmented intelligence (Aul), which blends human expertise with AI capabilities, emerges as a compelling paradigm (Troussas et al., 2025). Here, technology amplifies rather than replaces human decision-making, optimizing cognitive processes and cultivating creativity. In our research, we have viewed how AI-powered feedback can reveal patterns and potential; yet it is our professional discernment that guides meaningful interventions and supports student learning.

Unfortunately, the rapid integration of AI into educational settings continues to outpace scholars' abilities to research its role in assessment design and feedback processes. While AI provides natural opportunities to support authentic assessment, reflective learning, and personalized feedback, we still have limited understanding as to how to do this effectively considering AI as a collaborative partner seeking to supplement human judgment. The integration of human judgment + AI has the potential to enhance rather than deter from educational decision making, and the lack of literature available as well as a lack of understanding within academia creates a critical need to examine approaches that balance the utility of AI with the expertise and professional discretion of educators. This manuscript strives to add to the limited literature available focusing on the collaborative role of human judgment + AI within assessment design and implementation.

In this manuscript, we will articulate the importance of co-design, where AI and educators collaboratively shape assessment tools, and serve to champion feedback partnerships that enhance reflective practice for both students and faculty. We will argue that sustainable innovation in assessment hinges on this synergy, leveraging AI's analytic strengths while being anchored in human values and lived experience. Ultimately, the future of assessment in higher education lies not in choosing between AI and human judgment, but in their thoughtful integration, where Aul empowers educators and learners alike, and where our stories as practitioners illuminate the path forward.

This manuscript advances two complementary arguments. First, AI can be viewed as a co-designer, best utilized in collaboration with educators during assessment design rather than as an automated replacement for faculty expertise. Second, AI can function as a feedback partner that supports iterative reflection, metacognition, and self-regulated learning for both students and educators. These two arguments are unified through Aul, where AI contributes analytic capability while educators retain responsibility for pedagogical judgment, ethical decision making, and contextual interpretation.

Literature Review

AI and Augmented AI

AI broadly refers to computational systems designed to perform tasks that typically require human intelligence, including pattern recognition, prediction, language processing, and decision-making (Organization for Economic Co-operation and Development, 2019; Williamson & Eynon, 2020). Recent advances in AI in education, especially with machine learning and deep learning, have enabled these systems to analyze large, complex educational datasets and generate outputs such as automated

scoring, feedback, and performance predictions. Within student assessment, AI has been applied in multiple areas, including automated essay scoring, intelligent tutoring systems, and learning analytics dashboards that identify at-risk learners (UNESCO, 2021; Zawacki-Richter et al., 2019). In one example, Foster and Siddle (2020) evaluated a university learning analytics platform that generated "no-engagement" alerts for students who had not interacted with the learning management system. These alerts were effective in identifying first-year students at risk of poorer academic outcomes and outperformed demographic indicators alone. While these systems offer potential to improve efficiency, concerns persist regarding validity, transparency, algorithmic bias, and alignment with pedagogical goals, especially in high-stakes assessments (Williamson & Eynon, 2020).

Conversely, Aul emphasizes a human-centered approach in which AI systems are designed to enhance human judgment and expertise (French & Shim, 2025). In Aul frameworks, educators retain authority over assessment decisions while leveraging AI-generated insights to support evaluation, feedback, and instructional adaptation. This distinction is particularly important in educational assessment, where professional judgment, contextual understanding, and ethical considerations are essential to ensuring fairness and validity (Zawacki-Richter et al., 2019). Aul aligns with emerging best practices that advocate for collaborative decision-making between AI systems and educators, integrating efficiency with human oversight to improve both the quality and integrity of assessment processes. This distinction between AI and Aul establishes the foundation for viewing AI not as an autonomous evaluator but as a collaborative partner that enhances educator judgment throughout assessment design and feedback.

Landscape of Digital Pedagogy

Digital pedagogy is a digital technology empowered teaching approach that has potential to transform the teaching and learning process by focusing not only on faculty's abilities to engage in digital instruction but also on students' abilities to use technology within the learning environment (Huang et al., 2024). The evolution of digital pedagogy, sometimes referred to as digital technology, is constantly evolving and changing to embrace the advancement of AI and other technologies. Digital pedagogy is no longer just about using online tools and platforms but is a "complex ecosystem characterized by artificial intelligence (AI), learning analytics, and adaptive learning systems" (Thompson & Fernandes, 2025, p. 1). Digital pedagogy is being reshaped to encourage educators to focus less on individual components, such as AI tools and learning analytics, and instead striving to embrace how these elements make up an integrated system (Thompson & Fernandes, 2025).

In more recent years, generative AI (GenAI) has pushed the envelope even further by supporting educators' efforts to move beyond the utilization of simple digital tools to framing GenAI as a collaborator or co-designer (Looi, 2024; Thompson & Fernandes, 2025; Zeivots et al., 2025). Digital pedagogy tasks educators to look beyond superficial utilization such as content generation and automation, but to see GenAI as a central component of today's educational system. However, for this collaboration to be successful, it is helpful for educators to consider how human and non-human elements interact to achieve a shared understanding as to how each component can support the other. This synergy has the potential to support educators in reshaping the instructional design process, enhancing learner engagement, and strengthening knowledge construction (Thompson &

Fernandes, 2025). Furthermore, it is helpful for educators to view AI and learning analytics not as separate entities but as a whole. While AI tools such as GenAI, intelligent tutoring, and automated assessment supports efforts towards personalized learning (Huang et al., 2024), the learning analytics associated with these efforts are key to formulating data-informed decisions when considering student behavior, performance, or engagement. By looking at AI and learning analytics in tandem, educators have the information necessary to help them think beyond a “one-size-fits-all” model of learning to one that is adaptive and personalized (Thompson & Fernandes, 2025).

Viewed as an active participant, GenAI can “mediate, prompt, and reshape inquiry, with effects that are methodological, epistemic and ethical” (Zeivots et al., 2025, p. 1337). Transitioning one’s mindset to viewing AI as a co-designer rather than as a tool can push educators to reexamine their role as well as how this partnership will reframe authorship, agency, and meaning making. By embracing GenAI as a co-designer, this technology can support faculty’s efforts in reimagining the curriculum, redesigning learning environments, as well as supporting larger, institutional change (Zeivots et al., 2025).

For those willing to embrace this synergy, it is helpful to consider the role of co-intelligence within this process. Co-intelligence refers to the blend of human sense making and GenAI’s ability to recognize patterns. This complementary relationship demonstrates the importance of blending these elements to support an integrated approach to teaching and learning. While GenAI can produce content, it is often flawed or incomplete which requires the human element to fill in the gaps that the technology cannot simulate without the context of an individual’s lived experiences (Looi, 2024; Zeivots et al., 2025).

AI Tools to Support Assessment Design and Feedback Processes

AI tools can support assessment design by enabling more adaptive, accessible, and data-informed approaches to evaluating student learning. These technologies become most valuable when they serve as collaborators within educator-led assessment design. Contemporary AI systems, particularly large language model (LLM)-based tools such as ChatGPT (OpenAI, 2026), Claude (Anthropic, 2026), and Gemini (Google, 2026a), can assist educators in generating assessment items, aligning tasks with learning outcomes, and constructing detailed rubrics that enhance validity and transparency. de Lima Lopes et al. (2026) found that multiple-choice examination items generated by ChatGPT for undergraduate medical education were accepted by faculty as largely accurate and appropriately aligned with intended cognitive levels. In addition, specialized tools such as QuestionWell (QuestionWell, 2025) and Quizgecko (Quizgecko, 2025) allow instructors to efficiently transform instructional materials into formative assessments, while platforms like Gradescope (Turnitin, 2026a) support rubric grading and improve consistency in evaluation. Gemini Notebook (Google, 2026b), an AI tool designed to help generate study guides, outlines, and drafts, is considered a closed-loop AI system; it only uses the documents the user uploads to answer question prompts, working within the existing information instead of pulling in outside sources as an open-loop system would. A recent systematic review found that AI is most frequently used in higher education for assessment and evaluation, as well as personalized feedback and recommendations for learners (Luo et al., 2025). Collectively, these tools enable the development of more authentic, context-rich assessments that better capture higher-order thinking skills.

AI tools also play a transformative role in facilitating feedback processes, particularly by improving the timeliness, consistency, and personalization of feedback. Automated feedback systems such as Turnitin Feedback Studio (Turnitin, 2026b) and Grammarly (Grammarly, 2026) provide immediate, AI-generated feedback on writing quality, organization, and originality, supporting skill development in writing. Additionally, AI-enabled platforms such as Canvas (with AI integrations) (Instructure, 2026) synthesize student performance data into actionable insights, allowing both learners and instructors to identify gaps and adjust learning strategies in real time (Latif et al., 2024). Despite these advancements, human oversight is important to ensure feedback accuracy, mitigate bias, and maintain alignment with intended learning outcomes, reinforcing the role of AI as an augmentation of instructor expertise, rather than a replacement.

AI as Co-Designer

Authentic Assessment

Role of AI as a Support System for Human Judgment

As AI continues to build momentum within higher education, a key consideration is how AI and humans can work collaboratively to provide the best learning experiences for the students we serve. While the integration of AI tools by educators is becoming more commonplace, many see them as tools for content generation and fail to align these practices to established instructional models. Human+AI collaborations encourage educators to move beyond serving as the primary source of knowledge to acting as a facilitator and mentor, allowing educators to focus on supporting students' critical thinking skills, creativity, and emotional intelligence (Chiu & Rospigliosi, 2025). By including GenAI and its associated tools into course development, faculty are more likely to strengthen their process for outcome-driven instructional planning (Dogan, 2025). One instance of this potential collaboration is utilizing Google Notebook LM (now known as Gemini Notebook) to craft learning outcomes associated with course readings and lecture materials. One author of this manuscript was tasked with redesigning a graduate-level sports management course. In this process, she recognized that students had not been previously made aware of how the course's learning outcomes aligned with the weekly assigned readings. She used Google Notebook LM to synthesize the reading materials and enhance her efforts to map the readings to the course learning outcomes as well as to identify any gaps that were present between the assignments and the course outcomes.

This human+AI collaboration is often referred to as post-digital co-design, which focuses on the collaborations and/or interactions that occur between human and non-human elements within the curriculum, including digital and non-digital engagement (Zeivots et al., 2025). Post-digital co-design tasks educators with looking beyond how AI tools can supplement human elements to exploring use to support learning analytics and identify strategies for adapting learning systems (Thompson & Fernandes, 2025). In one example in nursing education, faculty and students co-designed an AI-powered learning analytics dashboard that synthesized performance data to identify learning needs and inform post-simulation instruction. AI supported instructional changes while educators retained responsibility for interpreting results and determining appropriate responses (Alfredo et al., 2025). Specifically, this relationship looks at GenAI as a co-designer “not as a matter of incorporating a new

technological tool but of reconceptualizing co-design as a practice shaped by and shaping complex assemblages of humans, technologies, and cultural contexts” (Zeivots et al., 2025, p. 1335).

The dynamic nature of AI not only challenges educators with using AI tools to enhance learning experiences, but also with exploring how AI influences assessment design. For example, one author of this manuscript and her colleagues have incorporated GenAI into the assessment development process by using an enterprise version of the AI platform to pre-test examination items before they are administered to students. Faculty ask AI to “take the test” or respond to individual questions, then compare its reasoning with the intended construct and keyed response. This process can reveal issues that may be difficult to recognize during traditional faculty review, including ambiguous wording, multiple plausible answers, and unintended clues. It can also draw attention to items for which the keyed answer may not be clearly defensible. Importantly, the AI response is not treated as evidence that an item is correct or flawed, but as an additional perspective that prompts faculty to reconsider how a question may be interpreted.

Bloom’s Taxonomy has long served as the guide for how educators think about assessing student learning (Bloom et al., 1956), but with the integration of GenAI, Oregon State University (2024) proposed a revised model that considers this technology. The Bloom’s Taxonomy Revisited framework was created to support ongoing reflection of how courses may need to be changed or updated to facilitate thoughtful integration of GenAI. The six levels of learning are divided into two themes: distinctive human skills and how GenAI can supplement learning. The distinctive human skills theme highlights areas that may require faculty engagement to assess dimensions that cannot be effectively evaluated through AI, while the second theme suggests strategies that GenAI can provide to support student learning, freeing faculty to focus on skills requiring a human touch (Oregon State University, 2024).

With this framework in mind, it is helpful for faculty to consider how AI can act as a collaborator to inform and support assessment approaches. For example, when considering the “Create” level of Bloom’s Taxonomy, faculty could partner with instructional designers to develop an AI chatbot within the learning management system that supports students as they navigate assignments such as case studies. Rather than developing the student’s response, the chatbot would help students identify connections between course content and the larger assignment, fostering holistic review and remediation where needed. In practice, one of this manuscript’s authors partnered with instructional designers to create an AI-powered chatbot embedded within the learning management system. The chatbot was intentionally designed to support learners completing the development of a milestone assessment by helping them connect course materials and content to assignment expectations. As the intent of the chatbot was to be resource-based rather than content-generating, the chatbot acts as a guide to support learners through a series of prompts that encourage synthesis of key concepts, identification of knowledge gaps, and as an impetus to review relevant course materials. Building off the revised Bloom’s Taxonomy framework, Page et al. (2024) proposed the Assessment Framework for Generative AI, which guides the development of formative and summative assessments by considering both Bloom’s Taxonomy level and knowledge dimensions. For example, at the “Evaluate” level, students may ask AI to assess a speech or presentation for strengths and weaknesses as a formative

assignment. For a summative assessment, students might write an argumentative essay and then ask AI to critique their work prior to revision and submission (Page et al., 2024). This combination of AI and human engagement encourages learners to use AI responsibly and productively throughout the assessment process rather than relying on it to complete the work.

Cultivating Creativity

In addition to supporting authentic assessment design, AI can play a pivotal role in cultivating creativity within assessment frameworks. GenAI systems can support creative processes by offering idea prompts, alternative perspectives, and iterative feedback (Kasneci et al., 2023). When used effectively, these tools can act as partners to expand learners' creativity. For example, one of the authors of this manuscript integrated the use of AI within a graduate-level course to support the development of a social media campaign. Students were encouraged to use AI to create social media ads that aligned with the narrative description of their designed campaign. This assessment activity supported students that may not have the creative skill to render a social media ad using traditional mediums such as hand drawing or computer graphics.

Empirical research suggests that AI assistance can enhance creativity by providing “cognitive resources” that support idea generation and problem framing, particularly for individuals with strong metacognitive skills (Sun et al., 2025). Metacognition refers to learners' awareness of and ability to regulate their own thinking, including reflecting on understanding, identifying misconceptions, and adapting strategies in response to feedback and performance outcomes (Van den Boom et al., 2007). In assessment contexts, this can be achieved through tasks that ask learners to co-create artifacts with AI, reflect on the co-creation process, and iteratively refine their work. Such approaches shift assessment from evaluation of concrete responses to process-oriented inquiry, emphasizing originality, adaptability, and engagement.

However, cultivating creativity through AI-enhanced assessment requires careful calibration. AI-generated output may risk homogenization of information or over-reliance on algorithm-generated ideas. To address this, assessment strategies should emphasize originality, require individual interpretation, and integrate reflective components that showcase learners' unique contributions. Further, instructors should frame AI as a tool for exploration and augmentation rather than as a substitute for learners' efforts.

Reflective Practice

Optimizing Cognitive Processes

AI-supported assessment design can optimize key cognitive processes, including metacognition, critical thinking, and self-regulated learning (SRL). One effective strategy involves using AI-driven feedback to scaffold learners' thinking by prompting reflection, clarifying misconceptions, and guiding continuous problem-solving. Evidence suggests that AI-assisted feedback can enhance reflective processes, self-regulated learning, and components of critical thinking when intentionally integrated into instructional activities and supported by effective pedagogical design (Nicol & Macfarlane-Dick, 2006; Zhan et al., 2025). One of this manuscript's author's experience with a teaching philosophy assignment provides an example of how GenAI can support deeper reflection and self-reflection during an assessment. Rather

than using AI to write the philosophy, learners engaged with a chatbot that served as a conversational partner to work through initial beliefs about teaching and learning. As the learner shared ideas based on initial prompts, AI posed follow-up questions that encouraged greater specificity and consideration of whether stated beliefs were reflected in actual teaching practices. For another example, a systematic review by Ba et al. (2025) found that AI-supported feedback systems can provide process-oriented and self-regulatory prompts that encourage learners to iteratively revise work, monitor progress, and evaluate their own reasoning rather than passively receiving corrective information. A useful conceptual framing for this work is the distinction between adaptive and static feedback systems in AI-augmented assessment. In an adaptive system, AI continuously monitors learner performance, provides immediate feedback, and adjusts subsequent tasks or prompts in response to learner actions. This cycle supports iterative skill development and calibration of learning (Qadir et al., 2025; Vorobyeva et al., 2025). In contrast, static systems provide AI-generated feedback without continuous adaptation. These systems are particularly valuable for encouraging reflection, exploration, and independent analysis because learners must determine how to interpret and apply the feedback. With intentional design, static interactions can support deeper metacognitive engagement by requiring learners to evaluate feedback, justify reasoning, and consider alternative approaches (Nicol & Macfarlane-Dick, 2006).

Adaptive feedback can also support cognitive load by calibrating task complexity and providing just-in-time support (Paas et al., 2003). Adaptive systems may reduce cognitive load through hints and spaced retrieval opportunities that encourage deeper processing and re-engagement with material (Lu et al., 2021; Mettler et al., 2020). Regardless, there remains a need to address potential cognitive offloading, where learners become overly reliant on AI-generated feedback (Risko & Gilbert, 2016). Assessment strategies should balance the efficiency of AI feedback with opportunities for learner reasoning, response justification, and critical evaluation. Research on SRL environments suggests that learners provided with prompts or partial feedback, rather than full solutions, demonstrate improved metacognitive monitoring and performance (Wang et al., 2023). When learners interpret feedback and generate their own revisions, they are more likely to engage in goal setting, error analysis, and strategic planning, all of which are critical components of deeper learning (Li & Zhang, 2021).

Formative Feedback Cycles for Deeper Learning

Formative feedback cycles supported by AI can strengthen deeper learning by operationalizing principles from constructivist learning theory, SRL, metacognition, and formative assessment pedagogy. Constructivist learning theory posits that learners actively construct knowledge through experience, reflection, and interaction with feedback rather than passively receiving information (Butler & Winne, 1995; Van den Boom et al., 2007). Grounded in Zimmerman's (2002) SRL framework, effective formative feedback promotes cyclical processes in which learners plan, monitor, evaluate, and adapt learning strategies over time.

AI-enhanced formative assessment environments extend these processes by providing immediate, iterative, and individualized feedback that helps learners continuously refine understanding and performance. Formative assessment pedagogy centers on the use of ongoing, actionable feedback to

improve learning during the instructional process, allowing students opportunities to revise, refine, and deepen understanding prior to summative evaluation (Butler & Winne, 1995).

Within these contexts, AI functions not as a replacement for instructor expertise, but as a co-designer and feedback partner that augments human judgment. Recent scholarship suggests that GenAI systems can provide scaffolded questioning, reflective prompts, and feedback that encourage students to engage more actively in revision, reflection, and meaning making (Dang et al., 2026; Hilliger et al., 2026). Additionally, formative feedback research has consistently demonstrated that students derive greater educational benefit when feedback is timely, iterative, and actionable rather than solely evaluative (Butler & Winne, 1995).

AI-Supported Feedback Processes

One particularly valuable contribution of AI within formative feedback cycles is its capacity for pattern recognition across large quantities of learner data. AI systems can identify recurring misconceptions, gaps in reasoning, patterns of disengagement, or trends in performance that may not be immediately visible to instructors (Latif et al., 2024; Luo et al., 2025). These analytic capabilities allow both faculty and learners to recognize trajectories of understanding over time and intervene earlier with targeted instructional support.

In addition, AI-enhanced feedback tools can encourage reflective practice by prompting learners to explain rationale, compare drafts, evaluate revisions, and articulate learning strategies, thereby strengthening metacognitive awareness and feedback literacy. Emerging evidence indicates that students who engage with AI as an interactive writing or reflection partner demonstrate greater engagement in self-monitoring and iterative revision (Nguyen & Nguyen, 2024; Salem, 2026). Dang et al. (2026) found that students engaging in dialogic writing interactions with AI demonstrated significantly greater self-regulation and reflective learning than students using AI primarily as an information provider.

However, the educational value of AI-mediated feedback depends heavily on pedagogical design and human facilitation. Effective implementation requires intentional instructor guidance to ensure that learners critically evaluate AI-generated feedback, engage authentically in reflection, and develop the judgment needed to distinguish between superficial and meaningful learning (Mendoza et al., 2026; Yilmaz et al., 2026).

Personalized Learning

AI-enhanced assessment becomes truly personalized when it is built on a well-developed model of how individual learners think and perform. Supervised and unsupervised machine learning, reinforcement learning, and learning analytics can be used to assess learner profiles, predict performance, and adjust task difficulty, feedback, and sequencing in real time (Hariyanto et al., 2025). These systems use clickstream data to evaluate response times and error patterns as indicators of learner knowledge and engagement, supporting adaptive assessments that provide continuous formative input.

For example, Giannakos et al. (2019) demonstrated that clickstream features collected during learning activities could accurately predict learner performance, supporting the use of behavioral data to inform adaptive learning and formative assessment. More advanced systems utilize affective or biometric data, such as eye movements and electroencephalography, to complement clickstream input and provide a more accurate assessment of learner progress and engagement than clickstream data alone (Giannakos et al., 2019).

Personalization is achieved when built upon a clear foundation of equity and inclusion. Reviews of AI-powered personalized learning emphasize that adaptive systems can either reduce or heighten existing inequities depending on how models are designed (Baker & Hawn, 2022; Shireesha & Jeevan, 2024; Vorobyeva et al., 2025). Baker and Hawn (2022) demonstrated that adaptive learning and predictive analytics systems may unintentionally reproduce educational disparities when trained on historically biased data, emphasizing that equitable personalization depends on intentional model design and evaluation.

When AI-driven assessment platforms are intentionally aligned with inclusive educational frameworks, they can offer tailored and scaffolded support, extended time, alternative formats, and targeted feedback for learners with disabilities or those from underserved communities while maintaining rigorous standards (Li et al., 2025). Case studies of AI-powered screen readers, adaptive interfaces, and intelligent tutoring systems have shown improvements in learner autonomy, engagement, and accessibility through individualized supports that preserve common curricular standards (Kooli & Chakraoui, 2025). As a result, AI-supported personalized learning has the potential to move assessment beyond a “one-size-fits-all” model toward experiences that are adaptive, inclusive, and responsive to individual learner needs.

Future of Assessment Development as a Cohesive Team

Best Practices

Acknowledging the role of AI in higher education is essential to ensure that institutions are prepared to adopt, utilize, and embrace how this technology will continue to shape learning moving forward. To adequately achieve these goals, institutions need forward thinking policies equipped to prepare faculty and students to safely and ethically use these technologies (Alawamleh et al., 2026). For educators, the development of policies specific to academic integrity could help to specify how LLM tools may be used in the learning environment (Perkins, 2023). These policies should also clearly articulate what constitutes academic misconduct or dishonesty as well as plagiarism and be widely distributed. Educating students on how AI tools can be used to enhance their learning and why they cannot replace aspects of the learning experience is important. Academic guidance can inform students of proper use, such as any limitations associated with AI, how to cite these tools when used, and examples of approved use as well as misuse (Perkins, 2023).

While cost-effective AI options may be readily available for students, higher education institutions must be prepared to allocate resources towards AI if they wish to embed AI-supported processes within the organization. Financial resources can vary greatly across institutions with smaller regional institutions, institutions located in low-income communities, or two-year colleges hosting smaller

budgets that limit the financial resources available to be dedicated to AI-associated costs (Hannan & Liu, 2021). These limited resources not only prevent students from experiencing AI-supported personalized learning but also limit opportunities to gain digital literacy that can be transferred into professional practice. An essential first step is for the institution to assess which AI tools will support the current priorities of the institution prior to dedicating funds towards these resources.

Because AI technologies are already embedded within the educational tools and environments that students and educators routinely use, avoiding AI is unlikely to preserve traditional approaches to teaching and learning; AI is unavoidable. Rather than attempting to exclude AI entirely, the focus needs to be on developing assessment strategies that intentionally integrate AI in ways that promote critical thinking, reflection, transparency, and learner agency. Similarly, studies on AI-supported reflective practice demonstrate that meaningful learning occurs not through passive reliance on AI outputs, but through iterative engagement with feedback, revision, and metacognition (Dang et al., 2026; Nguyen & Nguyen, 2024). Critically evaluating the output is imperative for ethical and transformative use of AI. Consequently, best practices for assessment increasingly emphasize designing authentic learning experiences in which students critically evaluate AI-generated information, document their reasoning, and demonstrate higher-order application of knowledge.

Successful implementation of AI in assessment depends not only on the availability of tools, but on educators' ability to align these tools with learning goals, maintain human oversight, and apply inclusive design principles in practice (Vorobyeva et al., 2025). To advance AI-augmented assessment, educators require support in developing the knowledge, skills, and confidence to co-design with AI effectively. This involves moving beyond technical training toward integrated professional development that emphasizes pedagogical alignment, ethical awareness, and practical application. Educators benefit from structured opportunities to engage with AI as a collaborative partner to experiment with prompt design, iteratively refine assessment tasks, and interpret AI-generated feedback through a disciplinary lens. Naturally, such efforts spotlight issues of bias, transparency, and equity, ensuring that educators are prepared to critically evaluate AI outputs and adapt them for diverse learners. A sustained commitment to this form of faculty development positions educators as purposeful designers of equitable, learner-centered assessment systems that harness AI to meaningfully enhance learning and feedback.

Preparing learners to use AI safely and effectively for assessment requires explicit instruction in AI literacy, clear expectations, and practice evaluating AI outputs. Literature emphasizes that students need to understand how AI works, how to use it appropriately, how to judge its outputs critically, and how to consider ethical issues such as bias, privacy, and accountability (Kasneci et al., 2023). In assessment settings, the focus needs to be on permitted uses, and required disclosure related to when and how AI was used. Further, faculty are challenged to design tasks that include reflection, critique, and comparison of AI-generated and human-generated work, rather than relying on detection or prohibition alone. Learners need to be taught to verify AI-generated output with credible sources, recognize hallucinations and limitations, and use AI as a support rather than as a substitute for their own reasoning (Kasneci et al., 2023; UNESCO, 2021). These approaches will help students develop the judgment needed to use AI responsibly while preserving academic integrity and authentic learning.

Educators need to be prepared for the ongoing evolution and implementation of AI in higher education. Emerging AI technologies are increasingly capable of generating adaptive assessments, providing real-time formative feedback, identifying patterns in learner performance, and supporting personalized learning pathways (Latif et al., 2024; Luo et al., 2025). As these tools become more integrated into educational environments, assessment can more easily extend beyond measuring recall to evaluating critical thinking, reflection, and problem-solving. As mentioned previously, contemporary scholarship suggests that the future of assessment will depend not on replacing educator expertise, but on leveraging AI to enhance human judgment, strengthen feedback, and create more authentic and responsive learning experiences that support self-regulated learning and metacognitive development (Dang et al., 2026; Yilmaz et al., 2026).

Future Considerations and Potential Areas for Concern

AI technologies are reshaping both academic and administrative functions in higher education, particularly through applications such as learning analytics, grading and assessment systems, and personalized educational support (Ahmad et al., 2022). Efficiencies associated with AI may also contribute to institutional cost savings through reduced grading time, improved feedback processes, and optimization of instructional resources. However, the integration of AI into assessment systems also carries significant financial considerations, including costs associated with software licensing, infrastructure development, faculty training, data security, and ongoing technological maintenance. Ahmad et al. (2022) emphasized that while AI-supported assessment systems can improve the effectiveness, accessibility, and responsiveness of evaluation practices, successful implementation requires thoughtful institutional investment and strategic planning to ensure equitable and sustainable adoption.

While higher education's willingness to adopt AI at the institutional level is changing, there are still opponents expressing concerns regarding the ethical implications of its integration (Gomathi, 2024; Mpolomoka, 2025). Most express concerns associated with privacy, bias, and transparency (Deepshikha, 2025; Marengo et al., 2024). AI-assisted assessment also raises significant privacy concerns because these systems may require students, faculty, or institutions to share personal information, proprietary materials, and professional expertise with third-party platforms. These concerns stem from the sheer volume of data AI accesses, especially data that includes behavioral patterns, personal information, as well as learning trajectories (Looi, 2024). In higher education, that data can include identifiable student records, draft work, assessment rubrics, internal program materials, and institution-specific knowledge that were not intended for model training or external retention. Researchers argue that GenAI systems create risks through unauthorized access or data breaches and through cloudy data practices, unclear retention policies, and the possibility that inputs may be repurposed to train external models (Pikhart & Al-Obaydi, 2025; UNESCO, 2021). This is especially concerning in assessment contexts, where instructors may upload confidential student work or sensitive examples to generate feedback. AI-assisted assessment should be governed by strict data-minimization principles, clear vendor contracts, and institutional guidance that protects student privacy, proprietary content, and professional expertise while preserving educational value (UNESCO, 2021). It is critical that higher education institutions ensure that data is protected to prevent unauthorized access and use (Marengo et al., 2024).

Beyond these initial privacy concerns are those associated with student use, and the challenges associated with discerning original student work and that produced by AI. Access to generated content becomes easier every day, allowing students to essentially outsource the development of critical educational achievements (Alawamleh et al., 2026). Faculty and administrators' tendency towards avoiding utilizing AI in the educational environment is understandable as concerns regarding cheating and plagiarism are valid (Looi, 2024), especially as research continues to show that AI created work is challenging to detect and that most existing systems are not equipped with accurately detecting it (Perkins, 2023).

Yet, while we as educators may be hesitant to fully adopt AI, it is essential that we continue to grow both our own as well as our students AI literacy (Marengo et al., 2024; Tzirides et al., 2024). This literacy "involves not only familiarizing oneself with the technical aspects of AI but also grasping its societal implications, ethical considerations, and the potential impact on various aspects of life, including education, employment, ethics, and privacy" (Looi, 2024, p. 482). As educators preparing students to enter the workforce, our limited understanding of AI and its potential long-term societal impact may provide a disservice to students by failing to prepare them for the professional world they will encounter (Aoun, 2024; Tzirides et al., 2024; Williams, 2024). Furthermore, enhancing faculty understanding of AI ideally supports their own autonomy as educators; increased AI literacy can result in improved viewpoints regarding the role of AI, positioning AI as a collaborator rather than as a replacement. This mindset shift strengthens rather than weakens the educator's professional identity and allows them to enhance the teaching and learning strategies they employ (Marengo et al., 2024).

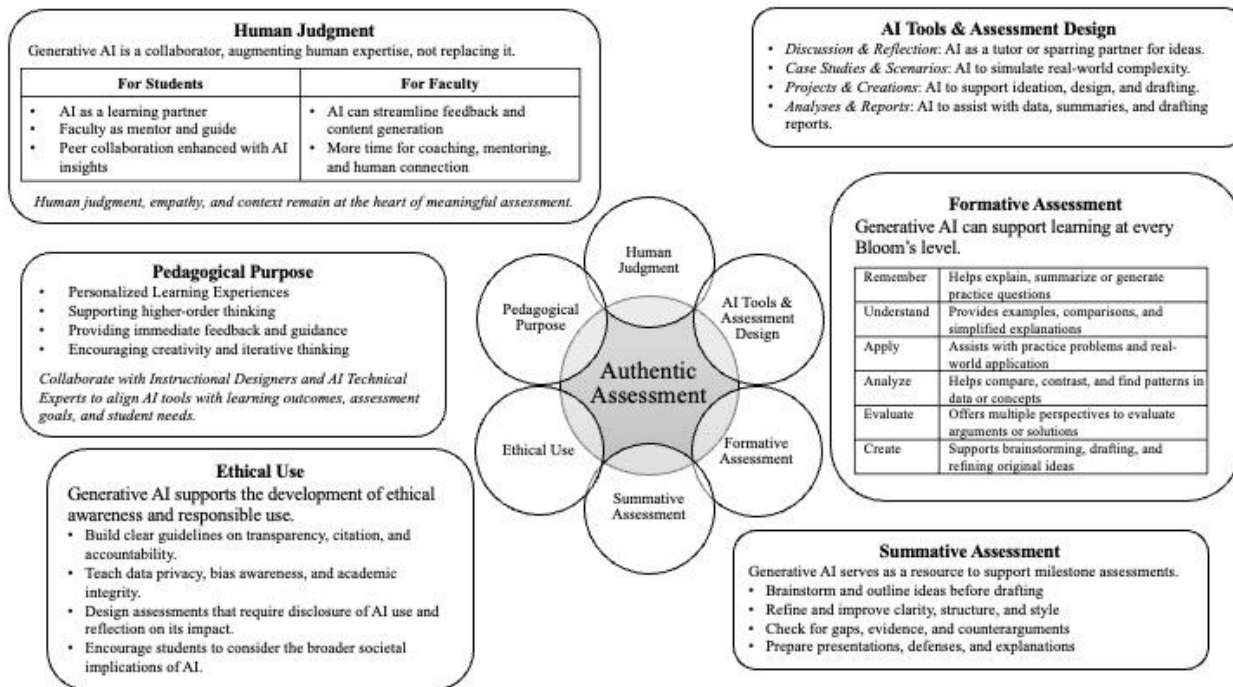
AI-assisted assessment carries a real risk of hallucinations, information that appears credible but is incorrect, incomplete, or fabricated. This is important because inaccurate output can mislead students and undermine the validity of the performance assessment. Learners may also spend additional time verifying output, which can increase cognitive load and reduce trust in the tool (Shi et al., 2025). Literature exploring GenAI in education warns that hallucinations are a central limitation of these systems and that inaccuracies may appear plausible and escape casual detection, making human verification essential in assessment contexts (Kasneci et al., 2023). In high-stakes assessments, AI platforms can improve learning outcomes and engagement, but researchers still caution that long-term effects and ethical risks require further validation, underscoring the need for careful oversight when AI shapes assessment decisions (Chen, 2025). For this reason, AI-assisted assessment should be framed as a supportive tool requiring checks for accuracy, source validation, and instructor review of outputs (Chen, 2025; Kasneci et al., 2023; Shi et al., 2025).

Lastly, it is important to recognize the overarching role AI will play in the future for the development of authentic assessments. In Figure 1, we propose the following framework to support this creation. Noted within the figure are six considerations, AI tools and assessment design, formative assessment, summative assessment, ethical use, pedagogical purpose, and human judgment, which when well thought out, craft an intentional and authentic assessment. Each consideration is broken down further within the surrounding boxes to provide further context, potential strategies or issues to consider, or examples of approaches. The integration of all six considerations supports faculty as they navigate the

complexity surrounding authentic assessment design and serve as an impetus for considering the hard questions as to the value and purpose of the assessment created.

Figure 1

Authentic Assessment Framework Considerations



Conclusion

The future of assessment will not be determined by increasingly sophisticated AI systems but by educators' willingness to engage AI as a thoughtful collaborator. When AI functions as a co-designer during assessment development and as a feedback partner throughout the learning process, it expands opportunities for authentic assessment, reflective practice, and personalized learning while preserving the human judgment that remains central to educational decision making. Ultimately, the greatest promise of AI lies not in replacing educators but in strengthening their capacity to design, interpret, and continuously improve learning.

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