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Integrating Artificial Intelligence Resources into Assessment: Utilizing the ACCELERATE Best Practices to Inform Assessment Development

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Abstract: Artificial intelligence (AI) has changed the landscape of higher education in an unprecedented manner. While many institutions of higher learning have not fully adopted AI into its infrastructure, faculty and students have begun to embrace the value it can bring into the teaching and learning environment. To successfully incorporate AI into educational practices, faculty and students must have access to the tools necessary to acquire the knowledge and skills needed to navigate its use in a safe and ethical manner. Drawing on the ten value-based commitments presented within ACCELERATE: Assessment Principles of Best Practice, this manuscript will examine how AI technologies can be leveraged to enhance assessment processes and outcomes. This manuscript will also explore how AI can support and extend assessment principles, ensuring practices remain relevant, equitable, and impactful in service of learning and organizational success.

Keywords: *ACCELERATE, artificial intelligence, assessment, faculty development, higher education, student learning*

Introduction

The transformative nature of artificial intelligence (AI) is unprecedented as it provides dynamic resources to support higher education not only within its basic administrative functions, but also through the adoption of adaptive learning systems that support individualized instruction, student performance assessment, and the integration of dynamic learning experiences (Siddiki et al., 2025; Mpolomoka, 2025). AI has revolutionized how educators navigate the teaching and learning environment, allowing them to reassess not only how students learn but also how their learning should be evaluated. Furthermore, AI technologies can create purposeful alignment by mapping assessments to institutional goals, learning outcomes, and accreditation requirements which supports mission-driven practices.

However, to successfully incorporate AI into educational practices, faculty instructors must be open to the adoption of AI into the learning environment, knowledgeable of best practices, and be prepared for the evolving technology surrounding its integration. Specifically, they must be open to how AI will

reshape their roles not only as educators but also in how they engage with students (Mpolomoka, 2025; Siddiki et al., 2025). Last, they must be prepared to consider any pedagogical, ethical, or resource associated limitations they may experience.

Drawing on the ten value-based commitments presented within ACCELERATE: Assessment Principles of Best Practice (Samuga_Gyaanam+Bheda et al., 2025), this manuscript will examine how AI technologies can be leveraged to enhance assessment processes and outcomes. AI integration offers new avenues for inclusive design, real-time responsiveness, and scalable solutions that have the ability to address diverse learner needs and organizational goals which will continue to reshape the educational landscape. We will also critically evaluate the opportunities and ethical/practice concerns associated with AI-driven assessment, while emphasizing the importance of human-focused approaches that foster trust, transparency, and continuous learning. Ultimately, this manuscript explores how AI can support and extend assessment principles, ensuring practices remain relevant, equitable, and impactful in service of learning and organizational success.

Literature Review

Define AI and Aul

In higher-education assessment, AI is often framed as a set of computational techniques, particularly machine learning and generative models, that can perform assessment-related functions, such as automated scoring, proctoring, plagiarism/authorship detection, and generated feedback, at scale (American Medical Association (AMA), 2024). Used this way, AI can shift core assessment labor from instructors to systems, sometimes substituting algorithmic outputs for human judgment in high-stakes decisions. In the setting of AI, the system becomes the controller, and the human is a moderator of this information. Because assessment quality depends on validity, reliability, and transparency, AI-forward implementations raise governance concerns such as unclear accountability for errors, opacity in model reasoning, bias amplification, and the risk that efficiency goals outpace pedagogical intent (UNESCO, 2021). Current international guidance emphasizes that education systems should adopt human-centered guardrails such as policies, oversight, and clear role delineation, particularly when AI tools meaningfully influence evaluative outcomes (UNESCO, 2021).

By contrast, augmented intelligence (Aul) in assessment emphasizes the partnership between AI and the human user, where the system is intentionally positioned as an assistive collaborator that strengthens educator expertise rather than replacing it (AMA, 2024; Alvarez-Icaza & Huerta, 2024). Aul prioritizes human oversight, ensuring instructors retain decisional authority while using AI for bounded tasks such as drafting rubric language, identifying patterns in item statistics, and flagging anomalies. In short, AI can be deployed to automate assessment judgments, whereas Aul utilizes AI to amplify educator judgment, centering interpretability, contestability, and professional accountability as core assessment requirements.

Importance of Assessment for Student Learning

Understanding how a learner processes information gained within the learning environment is essential to ensure that they are gaining the knowledge, skills, and attitudes necessary to transition into the professional world upon graduation. Assessing student learning “means collecting, analyzing information, interpreting, and acting on that information” specific to their academic performance in alignment with the expected learning goals (Ahmad et al., 2022, p. 3). Assessment, grading, and feedback are all considered critical elements of the educational process and, as such, serve as a guide to foster a conducive learning environment (Mpolomoka, 2025). Yet, while assessing student learning outcomes is generally an expectation of faculty responsibilities, they are often not trained to create, implement, and revise assessment strategies which can create a disconnect (Gordon & Smith, 2021).

Cope et al. (2021) note that “Assessment is perhaps the most significant area of opportunity offered by artificial intelligence for transformative change in education” (p. 1233). Due to the complexity of assessment practices, higher education is seeing a definitive divide in how assessments are selected, created, and utilized. Traditional assessments have the potential to raise issues such as concerns regarding validity, inherent biases, scalability issues, or inconsistencies both in administration and grading (Ahmad et al., 2022; Mpolomoka, 2025). The integration of AI tools and technologies can create a level of adaptability not present in traditional assessment structures (Ahmad et al., 2022), thus reducing the likelihood of these issues (Mpolomoka, 2025). AI’s inclusion also provides a more robust and continuous assessment of learning. This integration allows for an ongoing evaluation of student learning, rather than a singular snapshot (Cope et al., 2021). However, it is essential to see the integration of AI tools into the assessment process as a collaboration rather than a replacement for faculty. Student assessment strategies still require a human element to make sense of AI findings (Cope et al., 2021; Liang et al., 2025; Mpolomoka, 2025).

Overview of the AI and Aul tools used to assess SLOs

AI and Aul are now embedded across multiple layers of assessment in higher education, from automated scoring to learning analytics and generative tools that both students and instructors use in assessment-related work (Rezaei-Zadeh & Cerbin-Koczorowska, 2025). AI systems are used to grade or support grading of essays, short answers, and programming assignments, often through machine learning models trained on large datasets of human-marked work to improve scoring consistency, turnaround times, and personalization of feedback (Deepshikha, 2025; Mpolomoka, 2025). These assessment structures are increasingly integrated within learning management systems (LMS) and analytics dashboards that aggregate performance data, providing instructors and advisors with early alerts about students at risk of failure and enabling more targeted interventions (Alalawi et al., 2025; Mpolomoka, 2025). In parallel, generative AI tools such as large language models (LLMs) are used by students to brainstorm ideas, structure arguments, and to gain formative feedback on drafts, which has effectively blurred the line between assessment artifact and AI-supported co-production of work (Banihashem et al., 2024).

Among the most extensively studied applications are automated essay scoring (AES) and automated writing evaluation (AWE) (Rezaei-Zadeh & Cerbin-Koczorowska, 2025). Empirical studies demonstrate that AI systems can approximate human ratings under constrained conditions, yet concerns remain

regarding construct underrepresentation, differential performance across demographic groups, and limited transparency in scoring logic (Nouis et al., 2025). Construct underrepresentation occurs when an assessment captures only a fraction of what it claims to measure, limiting the validity and usefulness of the resulting scores. Recent studies on fairness in AES underscores the need to complete subgroup analyses and iterative auditing to prevent bias amplification, particularly when assessment results are high stakes (Litman et al., 2021). Importantly, reviews of AWE suggest that instructional benefit is maximized when AI-generated scores and feedback are mediated by instructors and embedded within formative assessment cycles, reinforcing the view that AI should support educational judgment rather than replace it (Fleckenstein et al., 2023; Nouis et al., 2025).

More recent research has shifted attention toward generative AI and its role in assessment and feedback. Emerging evidence suggests that LLMs can enhance the efficiency and specificity of formative feedback and support student self-regulation; however, it also introduces new risks related to transparency, hallucinations in feedback (Memarian & Doleck, 2024), and inconsistent alignment with assessment rubrics. Hallucinations refer to situations where a model generates information that is factually incorrect, fabricated, or unsupported by its training data. Consequently, both empirical research and international guidance increasingly advocate for Aul approaches, in which AI systems are deliberately positioned as assistive tools within human-in-the-loop assessment designs.

Assessment Best Practices Considering ACCELERATE and AI/Aul Support

Best practices for using AI in assessment are strengthened when they are intentionally guided by the ACCELERATE principles, which emphasize alignment, equity, learning-centeredness, and action-oriented use across the entire assessment lifecycle (Samuga_Gyaanam+Bheda et al., 2025). The acronym ACCELERATE represents the following ten principles: aligned purposefully (A), continuously cultivating (C), collaborative and co-creative (C), equity and empowerment-motivated (E), learning centered (L), energized by expertise (E), responsiveness-oriented (R), action driven (A), transparent and trustworthy (T), and enduring and evolving (E) (Samuga_Gyaanam+Bheda et al., 2025).

In a nutshell, ACCELERATE principles suggest that AI-enabled assessments be purposefully aligned with institutional values, learning outcomes, and community needs, rather than adopted solely for efficiency or innovation. AI tools and systems should iteratively inform curricular, programmatic, and policy-level improvements, not merely generate data for compliance. Consistent with ACCELERATE's emphasis on collaboration, learners, faculty, and other stakeholders should be meaningfully engaged in the design, interpretation, and use of AI-generated assessment evidence, particularly when decisions may impact access, progression, or opportunity. AI outputs should be critically examined for bias, transparency, and impact, ensuring that assessment serves as a mechanism for reducing – rather than reinforcing – inequities. Finally, ACCELERATE underscores that assessment must be learning-centered and action-driven; thus, AI-enabled insights should translate into timely feedback, instructional adaptation, and documented decision-making processes that improve learning environments and organizational effectiveness over time. (Samuga_Gyaanam+Bheda et al., 2025)

In the following sections, we will critically evaluate the opportunities as well as any ethical or practical concerns associated with AI-driven assessment practices, while emphasizing the importance of human-focused approaches that promote trust, transparency, and continuous learning. Specifically, we will examine which elements of the ACCELERATE best practices align with findings to support the utilization of AI within academic assessment. For clarity, authors will use AI tools as a consistent term throughout this manuscript which will encompass both AI-assisted tools and Aul-assisted tools.

Programmatic Outcomes and Curriculum Mapping to Support Assessment Development

Assessing student learning outcomes has multiple purposes within higher education. First, is to evaluate how a student's knowledge, skills and abilities have improved or changed over time, and second, to achieve the institution's goal to produce practice ready graduates. To achieve this second goal, it is crucial that educators map student learning outcomes to program goals as well (Harden, 2001). Curriculum mapping is a fundamental element of understanding if the program is achieving its intent and to support students as they navigate the expectations of their academic program which reconciles with the first element of ACCELERATE, aligned purposefully. While this process can be challenging in the best of circumstances, it is essential as it allows students, educators, and administrators to see the alignment between goals/objectives, educational methods, implementation, and evaluation (Raskob et al., 2025).

The incorporation of AI can be used to streamline the curricular mapping process by reducing this time intensive endeavor and faculty burden (Ng et al., 2025). By adopting AI into the process, it also decreases the likelihood of a fragmented map that focuses primarily on the alignment of the curriculum to the goals of the institution rather than student needs. Raskob et al. (2025) examined how AI could assist in curriculum mapping when faced with accreditation requirement changes to support timely curricular revisions when changes occurred within discipline-specific accreditation requirements. They found that the integration of AI into the curriculum mapping process reduced task completion time by two days and identified issues that were overlooked by human reviewers. Specifically, the output created by the LLM generated a report that highlighted updated as well as new requirements, while also identifying critical differences between the previous and current accreditation requirements.

A well mapped curriculum is essential to ensure that students enrolled within the academic program are practice-ready upon graduation. Curriculum mapping supports positive student outcomes as its transparency allows learners to see linkages between the various elements of the curriculum such as learning outcomes and assessment measures (Harden, 2001). The integration of AI into the curriculum mapping process supports positive student learning as it also has the ability to identify gaps within the curriculum to make educators aware of where they are present. This identification of gaps allows educators to pivot within the curriculum to support learners to ensure they are prepared in these identified areas. Furthermore, with the integration of curriculum mapping into LMS as well as assessment software, students have access to performance metrics which serve as roadmaps where they have experienced performance gaps to support their goal of continuous improvement prior to reassessment.

As faculty utilize AI to map the curriculum, a crucial next step includes considering how AI should be integrated into the curriculum. The debate of allowing AI utilization for student submissions continues to be explored and we, as educators, should recognize that encouraging students to utilize AI tools can reposition them from passive to active partners. Additionally, faculty are continually challenged with managing the unmitigated use of AI by students and discerning a student's authentic work from AI-crafted narratives (Liang et al., 2025; Williams, 2025). A strategic approach in which to overcome these challenges is to safely prepare students to utilize AI within the curriculum so that they may transfer these discernable skills into real-world settings. AI must be integrated into the curriculum as well as then be assessed on knowledge gained using these tools. This inclusion of AI tools allows students to practice using these in a safe and controlled environment (Williams, 2025). Furthermore, transparency about ethical uses of AI in assessment should be taught to students as the workplace expects their future employees to be trained and equipped to use AI ethically once employed (Aoun, 2024; Williams, 2025).

Supporting Faculty Adoption and Development

Supporting faculty adoption and development is essential for effective AI-integrated assessment and aligns closely with the principles of the ACCELERATE framework, especially with its emphasis on collaborative innovation, actionable implementation, and continuous learning. Faculty function as the bridge between AI technologies and pedagogically sound assessment practices, so targeted professional development on AI literacy, ethical applications, and assessment design is needed. Ahlam et al. (2025) found that targeted training specifically focused on introducing faculty to AI tools and effective prompt development can lead to improved proficiency. Such training not only enhances technical skill acquisition but also increases faculty's willingness to participate in AI-driven assessment practices (Gomathi, 2024), increasing the potential for the development of valid and meaningful assessment strategies.

Professional development must also focus on ensuring assessment tools are developed using equity and empowerment-motivated approaches. Such approaches require faculty to critically evaluate how AI systems reproduce or amplify existing biases and to intentionally design assessments that promote inclusivity, accessibility, and fairness. This includes training educators to scrutinize training data for sources of bias, apply principles of universal design, and implement auditing processes to detect disparate outcomes (Zawacki-Richter et al, 2019). Further, faculty must be prepared to clearly communicate how AI tools are used in assessment and interpret outputs responsibly.

A crucial element for successful adoption of AI into teaching practices includes having a strong understanding of faculty and administrative perspectives regarding AI tools and their potential usefulness. Development must support faculty and administrative understanding of how AI tools can assist with managing routine, low-level grading details, freeing cognitive bandwidth for high-value pedagogical activities such as mentoring and curriculum innovation. A study conducted by Gomathi (2024) found that faculty backgrounds are an indicator of their readiness or willingness to adopt AI tools into their teaching practices. This same study showed that faculty are more likely to embrace AI when its use is clearly aligned with institutional goals, as this alignment signals the strategic importance of technology in advancing broader organizational objectives (Gomathi, 2024). Collectively,

these findings underscore the importance of aligning faculty development initiatives with both individual needs and institutional priorities to support meaningful and sustained AI adoption.

Assessment utilizing AI has the potential to meaningfully advance collaborative and co-creative practices by broadening who participates in assessment design, interpretation, and use. Consistent with this ACCELERATE principle, AI systems can aggregate and synthesize input from learners, faculty, and practice partners, allowing assessment to reflect multiple perspectives rather than a single lens (Samuga_Gyaanam+Bheda et al., 2025). AI can also create exam items for faculty review, as well as suggest refinements of scenarios, rubrics, and feedback prior to implementation. These capabilities support iterative, team-based development in which stakeholders can rapidly prototype, critique, and refine materials, strengthening both relevance and validity.

The evolving nature of AI and the educational landscape challenges faculty with embracing the roles of lifelong learners. Changing student expectations, industry demands, and rapid technological advancement require educators to remain deeply grounded in their disciplines while simultaneously developing expertise in evidence-based teaching and learning practices to maintain relevance within the academy. This expanding expectation aligns closely with the ACCELERATE framework's principle of being energized by expertise, as faculty are called to continuously build and apply specialized knowledge in both pedagogy and emerging technologies to drive meaningful innovation in assessment. As AI becomes increasingly integrated into learning environments and student assessment, faculty must develop additional expertise to both use these technologies effectively and recognize when their own professional judgment should take precedence in evaluating student progression. Without adequate training and institutional support, action-driven systems risk shifting responsibility for instructional decisions to technology, thereby diminishing professional judgment rather than strengthening it (Lee et al., 2024).

Student Learning Outcomes Assessment and Student Feedback

Student learning outcomes (SLOs) are explicit statements that define what learners are expected to know, be able to do, or value by the end of a course or program. They are written in measurable, observable terms to guide instructional design, learning activities, and assessment strategies. Well-constructed SLOs align with broader programmatic goals and accreditation standards, ensuring coherence across the curriculum. They are the necessary starting point for purposefully aligned assessments. They also provide a transparent framework for evaluating student performance and continuous improvement of teaching and learning, making them necessary for a continuously cultivating and learning-centered assessment environment.

A SLO-centered approach to assessment requires intentional alignment among learning goals, assessment design, measurement strategies, and feedback processes. Within the ACCELERATE framework, learner-centered assessment emphasizes the role of feedback as foundational to student learning, positioning assessment not as a concluding event but as part of an ongoing developmental process. Embedding AI into formative assessment design supports this alignment by enabling continuous collection and analysis of performance data that can be used to refine both instruction and learning in real time. Rather than evaluating past performance alone, AI-integrated systems facilitate

iterative, low-stakes practice and data-informed refinement, accelerating skill development and promoting learner agency. However, to maintain trust and engagement, it is essential that educators clearly communicate how AI informs assessment design, interpretation, and decision-making, particularly in collaborative learning environments where misperceptions might arise.

AI tools enhance the design and measurement of SLOs by enabling more adaptive, and authentic assessment strategies. Adaptive formative assessments, such as AI-driven quizzes and case-based simulations, dynamically adjust item difficulty and sequencing based on learner performance, ensuring that assessment tasks remain aligned with individual readiness levels (Deepshikha, 2025). Natural language processing tools further support measurement of complex outcomes by analyzing written responses, clinical reasoning, and reflections for organization, conceptual accuracy, and alignment with learning objectives, while pattern recognition algorithms identify common errors across cohorts to guide targeted remediation (Deepshikha, 2025). In competency-based curricula and large-enrollment environments, intelligent tutoring systems and custom generative pre-trained transformer (GPT) feedback tools enable iterative dialogue around extended responses, allowing students to submit work, receive targeted feedback, and clarify misunderstandings within a single session (Paladines & Ramirez, 2020). These approaches strengthen the validity of SLO assessment by capturing higher-order thinking and performance over time rather than relying on single-point evaluations.

Performance-based assessment modalities are particularly well aligned with SLO frameworks, as they generate rich, process-oriented data that reflect authentic application of knowledge and skills. In health professions education, approaches such as objective structured clinical examinations (OSCEs), virtual patient encounters, and AI-enabled simulations allow learners to engage in realistic clinical tasks within controlled environments (Cook et al., 2011; Issenberg et al., 2005; Swiecki et al., 2022). Simulation-based assessment addresses practical and ethical constraints of real-world practice while preserving fidelity and enabling repeated practice. AI further amplifies these approaches by automating data capture and enabling longitudinal analysis of learner decisions, behaviors, and performance trajectories, thereby supporting alignment among learning outcomes, instructional strategies, and assessment practices (Chan & Zary, 2019). This responsiveness-oriented approach positions AI-enabled simulation as a key mechanism not only for individual assessment but also for programmatic evaluation and curricular refinement (Mpolomoka, 2025; Zhao, 2024).

Central to a SLO-driven framework is the feedback loop, where assessment data are translated into actionable insights that guide learning. AI-supported feedback systems enhance this process by improving the timeliness, specificity, and personalization of feedback. Intelligent tutoring systems, writing assistants, and AI-driven formative platforms provide just-in-time feedback that is not constrained by instructional setting and may exceed the efficiency of traditional classroom-based feedback models (Kestin et al., 2025). Within the ACCELERATE framework, this aligns with an action-driven orientation in which AI transforms static feedback into actionable guidance, specifying next steps such as targeted practice, revised priorities, and recommended resources. Additionally, AI tools can integrate feedback from multiple sources, such as instructors, peers, and learners themselves, to enhance the depth and relevance of feedback while promoting collaboration, transparency, and assessment literacy (Ifenthaler & Yau, 2020; Nicol et al., 2014; Tai et al., 2018). Iterative cycles of low-

stakes assessment combined with immediate, personalized feedback support self-regulated learning and sustained competency development (González-Calatyud et al., 2021; Nicol & Macfarlane-Dick, 2006). This focus ensures assessments are enduring and evolving.

AI also strengthens the continuous improvement and quality assurance dimensions of SLO assessment. Learning analytics dashboards convert raw performance data into actionable insights, including identification of at-risk learners, patterns of misconception, and recommended interventions, thereby shifting assessment from retrospective evaluation to proactive planning. Automated grading systems within LMS and platforms such as ExamSoft enable efficient analysis of item-level performance data, allowing educators to identify flawed questions, refine assessments, and ensure purposeful alignment with intended learning outcomes (Ifenthaler & Yau, 2020). These capabilities enhance the consistency, transparency, and scalability of assessment practices, addressing longstanding challenges such as grading variability and limited insight into student learning (Mpolomoka, 2025; Williams, 2025). Moreover, AI-supported assessment strategies can increase authenticity by capturing more comprehensive representations of student learning and preparing learners to engage with technologies reflective of contemporary professional practice (Williams, 2025; Yeadon et al., 2023).

Finally, the integration of AI into SLO assessment frameworks supports replicability and sustainability across diverse educational contexts. AI enables the generation of customized assessments tailored to individual learner needs, allowing faculty to move beyond one-size-fits-all approaches and better capture true student understanding (Cotton et al., 2024). At the same time, ensuring transparency and trustworthiness requires clearly articulated institutional policies guiding the ethical and effective use of AI in assessment (Liang et al., 2025; Mpolomoka, 2025). When implemented with appropriate oversight, AI serves not as a replacement for educator expertise but as a powerful augmentation that enhances alignment, feedback, and continuous improvement within student learning outcomes assessment.

AI Challenges and Potential Limitations

While this integration of AI into assessment practices has its benefits, we would be remiss to not also acknowledge potential challenges and limitations faculty and students may experience with this adoption. In the following sections, we will explore how the integration and the utilization of AI impacts faculty and students, specifically looking at challenges and potential limitations of this adoption. Furthermore, we will explore how faculty and students may have to adapt to and respond to this technology.

As previously discussed, the role of curricular mapping plays a key role in supporting the overall assessment practices within an academic program; yet the time needed to comprehensively map a curriculum can be quite intensive. The integration of LLMs into the curricular mapping process can result in reduced time to completion. However, the output generated is only as beneficial as the prompt used within the query. Raskob et al. (2025) noted within their findings the critical role the customized prompt played in the data generated and its usability within the decision-making process.

Preparing faculty and administrators to craft a comprehensive and targeted prompt will be a pivotal area for professional development.

Faculty should also recognize that AI ought to be viewed as support rather than a replacement for their expertise. Despite its promise, collaborative AI (Human + AI) introduces risks if co-creation is superficial or unevenly distributed. The responsibility and accountability associated remains with the faculty, specifically as they “must contend with the consequences of their educational actions” and must ensure that their curricular choices meet the requirements and objectives of the program (Raskob et al., 2025, p. 8). Additionally, because AI does not replace judgement of experts, collaboration must be intentional and ethical to ensure that AI-supported co-creation does not unintentionally reinforce power imbalances, which aligns with the collaborative and co-creative expectations of the ACCELERATE framework.

The barriers to faculty willingness to widespread adoption of AI include feelings of inadequate support from the institution, limited access to training opportunities, ethical concerns specific to algorithmic bias and transparency, and fear of job displacement (Gomathi, 2024). The inclusion of technology is a double-edged sword as faculty workload is reduced, allowing them to redistribute their time to focus on other essential elements of their role (Cotton et al., 2024; Deepshikha, 2025). However, faculty will also need to spend some of the time gained to immerse themselves in the professional development efforts required to learn how to utilize AI. Further, monitoring student AI use creates additional oversight burden that may negate the time-saving aspects of AI feedback. While faculty recognize that training is needed to support this integration, they may not be aware of how to access those opportunities or may feel that the offerings are not appropriate for their learning level. Furthermore, educators must have access to the resources needed to integrate AI into the assessment process. Many educators may need guidance as to how these tools can be integrated into their courses and require additional assistance from other instructional groups such as instructional designers or centers for teaching and learning. The institution must be prepared to provide the resources necessary to support this adoption. This requires not only time release for training but a commitment to the financial costs associated. Last, faculty must be aware of any data concerns associated with the utilization of AI and be able to identify when AI may be generating inaccuracies or hallucinations.

The use of AI in performance-based assessment introduces notable challenges. AI systems depend on pre-specified metrics and models that may insufficiently capture clinical reasoning and judgment (Xu et al., 2025). Development costs, faculty time required for scenario design and validation, and ongoing system maintenance may pose barriers, particularly for resource-constrained programs. Importantly, AI cannot replace educators’ interpretive judgment or ethical responsibility in assessment. International guidance emphasizes that AI tools must be embedded within human-centered, transparent, and equitable governance frameworks to ensure privacy protection, mitigate bias, and prevent the amplification of existing inequities in assessment and decision-making (UNESCO, 2021; World Health Organization, 2023). Without intentional oversight, AI-driven assessment risks prioritizing efficiency over validity and trust.

If poorly designed, AI involvement risks devolving feedback into a stream of suggestions that feel generic or overwhelming, diluting their actionability. Despite its inherent benefits in response efficiency, AI introduces risks around over-automation, opacity, and equity that must be explicitly managed. Responsiveness can be undermined if feedback is inaccurate, generic, or misaligned with disciplinary standards (Chai et al., 2024). Without clear links to criteria and examples, students may see AI advice as abstract rather than as concrete steps tied to specific learning outcomes. Furthermore, learner-centered AI assessment carries significant challenges specifically surrounding automated written feedback (AWF), where AI systems provide automated feedback on written work without direct authorship by the educator. Studies evaluating AWF describe bias, lack of control of quality of output, and security concerns as critical risks that could impact assessment validity and reliability (Arslan et al., 2024). Despite these challenges, evidence suggests that AWF systems can support and, in some cases, directly track student growth over time. AWF platforms frequently generate repeated writing quality scores that allow learners to monitor performance trajectories and calibrate progress (Fleckenstein et al., 2023). However, much of this growth detection remains anchored in revising text rather than higher-order constructs such as argument quality or conceptual sophistication.

Lack of transparency in assessment decisions makes identifying sources of errors or bias difficult and muddles explanations to students about how scores and feedback are generated (Arslan et al., 2024). Further, compared to human educator feedback, which typically addresses both language and content issues, AI feedback often covers fewer features of writing, suggesting potential construct underrepresentation (Strobl et al., 2019). Studies of AI-generated feedback demonstrate that, despite increases in volume and speed of assessment, completeness and precision can vary considerably, requiring human review to ensure students respond to accurate advice (Venter et al., 2025). In addition, over-reliance on automated analytics may shift the focus from rich, qualitative evidence of learning towards easily measurable constructs that provide superficial indicators of progress. Furthermore, action signals can become misdirected when predictive analytics and automated alerts flag student risk based on biased data. Instructors must act intentionally to avoid intervening unnecessarily or bypassing students requiring intervention. Finally, systemic risks include challenges related to algorithmic bias, data privacy, and transparency which could misidentify low- and high-performing students, reinforcing inequities. Teachers may lack the technical knowledge and institutional support needed to critically interpret AI dashboards and adapt instruction accordingly, so responsiveness can devolve into uncritical acceptance of system recommendations.

In addition to challenges in the assessment itself, over-reliance on AI may reduce teacher-student interactions and decrease the social and emotional aspects of learning that human feedback uniquely provides. Without educator engagement in the learning process, students may misinterpret feedback or become overly reliant on AI for self-assessment and development. Further, student learning approaches can be impacted when learners seek solutions directly from generative AI applications, which can undermine student effort and academic integrity if assessments are not carefully designed.

There are also faculty concerns regarding student use of AI to formulate assessments. These stem from fears that student performance is not truly represented. Each iteration of AI released demonstrates a decreased level of writing expected from the student. Research findings show that LLMs and other

iterative AI tools such as ChatGPT can generate logical and reasoned text that makes it challenging to distinguish whether the content generated was written by a human or AI (Liang et al., 2025; Williams, 2025). Perkins (2023) postulates that LLMs “represent a clear and potential threat to academic integrity as academic staff may be unable to correctly identify the amount of content produced by a student and therefore provide an accurate evaluation of a student’s comprehension and interpretation of the topic at hand” (p. 7). The integration of LLMs is further muddled by a lack of understanding in the academy of how its inclusion should be viewed; is it acceptable practice or should it be considered academic misconduct? There is ongoing debate as to whether AI tools should be considered an issue of academic integrity, with many institutions failing to make concrete decisions on how these issues should be handled. These decisions must be clearly articulated at the university-level, and all created policies should specify how LLM tools may be used and how this utilization should be notated (Perkins, 2023). Furthermore, there are also concerns of its utilization devaluing the academic degree (Cotton et al., 2024) but as higher education institutions have failed to come to a common consensus as to the appropriate role of AI in the academic space, assessing the overall impact of its utilization towards degree value will be an area of research for the future.

Conclusion

The alignment between AI-assisted assessments and ACCELERATE best practices is evident and demonstrates that the synergy of these two frameworks will support faculty as they strive to create authentic and intentional assessments. Although, faculty will require targeted professional development to acquire the knowledge and skills needed to utilize AI tools effectively. Higher education institutions will need to be prepared to manage the time commitment required for faculty to acquire these skill sets as well as the fiscal resources needed to integrate tools of this nature. Institutions will also need to be prepared to provide faculty and students with the resources necessary to safely utilize these tools and the infrastructure required (i.e., access to technology experts, technology platforms) to optimize this integration.

The intent of this paper was to explore how AI and Aul tools can be utilized to enhance assessment strategies within the teaching and learning environment, and how these strategies align with the ACCELERATE best practices. While research is still limited regarding the long-term impact the inclusion of AI tools can have in higher education, early data shows a correlation between AI-integration and positive engagement (Memarian & Dolack, 2024). These early findings are promising indicators of potential long-term benefits of this integration.

The acceptance and value of utilizing AI tools is growing, and widespread adoption of this technology within industry supports the need for higher education institutions to embrace this evolution of assessment. However, it is imperative that institutions make a definitive decision on how this technology will be implemented and regulated to ensure the ethical utilization of AI within institutions of higher education and to avoid potential allegation of misconduct. The establishment of consistent policies and procedures for its utilization among faculty and students is necessary to operationalize AI’s use on college campuses and to establish expectations to ensure that students understand the parameters for its utilization.

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