AI-Enabled Industry-Collaborative Assessment (AI-ICAM): Advancing Pedagogy and University–Industry Collaboration

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Abstract

This paper presents the AI-Enabled Industry-Collaborative Assessment Model (AI-ICAM), developed to integrate artificial intelligence into higher education assessment through authentic, industry-aligned tasks. Drawing on three case studies, the research examines how AI can enhance assessment design, delivery, and outcomes in partnership with industry stakeholders. The first case, an undergraduate sustainability and digital marketing module, demonstrated how students leveraged AI for creative campaign assets, improving alignment with client sustainability goals. The second case, a multidisciplinary "Biz-a-thon" innovation sprint with a financial technology partner, showed how AI-supported rapid prototyping improved time efficiency, presentation quality, and professional polish under time constraints. The third case, a curated podcast series with industry leaders, revealed that even indirect AI exposure through expert discourse could stimulate student engagement with emerging tools and trends. Cross-case analysis identified common benefits of AI integration, including enhanced creativity, efficiency, and professionalism, alongside variations in impact depending on whether AI use was direct or indirect. The findings highlight the importance of strategic alignment between AI capabilities, assessment objectives, and industry needs, underpinned by a culture of trust, ethical practice, and openness to innovation. The paper concludes with practical recommendations for refining AI-ICAM and advancing university–industry collaboration in assessment.

Keywords: artificial intelligence, higher education, assessment innovation, industry collaboration, sustainability education

Introduction

Assessment in higher education is undergoing significant change, yet many traditional approaches remain slow, rigid, and misaligned with professional demands. Brown (2022) noted that assessment methods have not kept pace with pedagogical advances, limiting responsiveness and flexibility. Examinations and fixed assignments tend to promote surface learning and reduce opportunities for authentic, applied learning tasks (Parmigiani et al., 2024). High-stakes summative exams have been shown to increase stress and may undermine real-world skill development (French et al., 2024). A lack of workplace-related, practical assessments contributes to a persistent graduate skills gap (Meylani, 2024; Whittaker, 2016). Embedding industry feedback and perspectives into assessment design has been found to strengthen alignment between academic learning and employability needs (Jackson et al., 2023; Richardson & Henschke, 2010).

In response to these challenges, universities are under increasing pressure to align assessment practices with professional competencies and the United Nations Sustainable Development Goals (SDGs). Artificial intelligence (AI) is emerging as a powerful enabler of personalised, adaptive, and real-time evaluation across disciplines. AI systems have been shown to tailor learning content and feedback to individual student needs, improving engagement and outcomes (Luo et al., 2025; Merino-Campos, 2025; Zhao, 2024). Adaptive learning systems are proving effective across fields including information technology, natural sciences, humanities, and agriculture (Li et al., 2024). AI-driven natural language processing tools now deliver immediate, nuanced, and scalable feedback, addressing the limitations of traditional grading (Gao et al., 2024; Kochmar et al., 2020). Frameworks such as Synthetic Educational Feedback Loops (SEFL) and related AI-enhanced systems have demonstrated high-quality, rapid assessment capabilities in varied learning contexts (Darvishi et al., 2024; Kovari, 2025).

Generative AI has also shown potential to improve both cognitive and emotional aspects of learning by providing supportive, personalised feedback that reduces negative affective responses (Alsaiari et al., 2025; Crompton & Burke, 2023). In writing and translation contexts, AI feedback has been shown to be reliable and effective, particularly when combined with human input (Luo et al., 2025). AI-enhanced collaborative learning environments have been linked to improved student performance, deeper engagement, and more effective peer interactions (Bond et al., 2024; Khong & Tanner, 2024).

This paper proposes the AI-Enabled Industry-Collaborative Assessment Model (AI-ICAM), which integrates AI-driven assessment with meaningful industry collaboration. Grounded in Constructive Alignment Theory and developed using a Design Science approach, the model aims to be scalable, ethical, and adaptable across disciplines.

Given the limitations of traditional assessment, the evolving capabilities of AI, and the increasing imperative for meaningful university–industry partnerships, this study is guided by the following research question:

How can AI be leveraged to design an assessment model in higher education that supports inclusive, adaptive pedagogy while fostering effective collaboration between universities and industry?

Aligning Assessment With Global and Professional Goals: Strategic Imperatives

The design of contemporary assessment models must begin with clarity about the learning outcomes they seek to achieve. Increasingly, these outcomes extend beyond disciplinary knowledge to encompass global competencies, sustainable development priorities, and workplace readiness. The United Nations Sustainable Development Goals (SDGs) provide a globally recognised framework for embedding sustainability principles into curricula, ensuring graduates are prepared to address complex societal and environmental challenges (Leal Filho et al., 2019). Embedding SDG-oriented learning outcomes in assessment has been shown to foster systems thinking, ethical reasoning, and the capacity for responsible innovation (Findler et al., 2019).

The call for responsible leadership competencies in higher education has gained momentum, with scholars emphasising skills such as ethical decision-making, stakeholder engagement, and sustainability literacy (Pless et al., 2012). Such competencies are increasingly prioritised by accreditation bodies and employers, who view them as essential for navigating interconnected global systems (Laasch et al., 2023; Pless & Maak, 2011). Research in management education confirms that embedding responsible leadership within assessment design supports ethical practice and contributes to long-term value creation in both public and private sectors (Maak et al., 2016).

Employer expectations are shifting towards graduates who can demonstrate transferable skills, adaptability, and cross-disciplinary collaboration (Jackson, 2016). This aligns with findings from employability research that link workplace success to problem-solving, digital literacy, and the ability to operate in diverse teams (Clarke, 2018). Studies show that structured career development learning embedded into curricula has a significant positive effect on students' perceived employability over time (Ho et al., 2023). Likewise, employability frameworks are evolving to emphasise 21st-century competencies such as adaptability, collaboration, and innovation, which can be directly supported by aligned assessment models (Eimer & Bohndick, 2023; Zainudden et al., 2022). This evolution strengthens the case for assessments that explicitly measure skills transferable across sectors and geographies (Tight, 2023). Accrediting agencies are responding to these demands by integrating industry-relevant competencies into their standards, which encourages assessment models that evaluate both technical and interpersonal capabilities (Coates et al., 2016).

Regulatory frameworks further reinforce the alignment of academic outcomes with professional standards, enhancing accountability and public trust. Evidence shows that transparent links between learning outcomes, industry needs, and assessment criteria strengthen graduate readiness and foster productive university–industry relationships (Oliver, 2015). These expectations extend beyond sector-specific qualifications to encompass societal contributions, with sustainability and employability increasingly recognised as quality benchmarks in higher education (Janssens et al., 2022). In this context, embedding employability into assessment is not only about job readiness but also about preparing graduates to adapt and thrive amid rapidly shifting labour market demands (Ho et al., 2023; Tight, 2023).

Taken together, these perspectives make clear that aligning assessment with global and professional goals is not merely an academic exercise but a strategic imperative. By grounding assessment in sustainability priorities, leadership competencies, and employer needs, universities can deliver graduates who are equipped to navigate complex challenges and contribute meaningfully to both their professions and society at large.

Building on these strategic imperatives, the next section outlines the pedagogical mechanisms of constructive alignment and co-creation that operationalise these goals in assessment.

Constructive Alignment and Knowledge Co-creation: Pedagogical Implementation

Constructive alignment, introduced by Biggs and Tang (2011), remains one of the most influential principles in assessment design. It advocates for a deliberate connection between intended learning outcomes, teaching activities, and assessment tasks so that all components work together to promote the desired competencies. This alignment transforms assessment from a final measurement into an integral part of the learning process, guiding students toward clearly articulated objectives and encouraging self-regulated learning (Boud & Molloy, 2013).

Within university–industry partnerships, constructive alignment becomes a vehicle for operationalising global and professional priorities in practical, discipline-specific contexts. Industry collaboration ensures that assessment criteria reflect current workplace practices, technologies, and problem-solving requirements (Perkmann et al., 2013). In such arrangements, students engage with authentic, applied challenges such as live client projects or industry-led simulations that mirror professional environments and test both technical and transferable skills (Jackson, 2016). When these partnerships are sustained over time, evidence suggests they contribute not only to immediate skill acquisition but also to improved graduate employability and long-term career outcomes (Ho et al., 2023; Huang, 2025).

Knowledge co-creation extends this alignment beyond curricular content to the design and delivery of assessment itself. Industry experts contribute applied insights and emerging trends, while academic staff ensure disciplinary depth, critical thinking, and methodological rigour (Ankrah & AL-Tabbaa, 2015). Co-created tasks, such as consultancy briefs, prototypes, or policy proposals, demand that students integrate theoretical understanding with practical execution, fostering innovation and adaptability (Bovill, 2020). Such collaboration often drives curriculum innovation, as insights from real-world contexts inform the continual updating of teaching content and assessment formats (Eimer & Bohndick, 2023).

Embedding co-creation in assessment design also supports diversity and inclusivity. By involving stakeholders from different sectors and communities, assessments can incorporate varied cultural perspectives, making them more equitable and reflective of global work contexts (Healey et al., 2014; Morris et al., 2021). This inclusivity promotes graduate preparedness for cross-cultural collaboration and strengthens the university's societal role (Robinson et al., 2020). Additionally, when industry and academia jointly shape assessments, they create an environment of mutual trust and sustained collaboration, with long-term benefits for both curriculum relevance and institutional networks (Huang, 2025).

Constructive alignment coupled with co-creation helps institutions demonstrate the measurable impact of their graduates' capabilities to accrediting bodies and employers. Universities that successfully integrate academic rigour with industry relevance not only enhance their reputation but also create a sustainable feedback loop between education and professional practice (Oliver, 2015). In this way, constructive alignment becomes both a pedagogical strategy and a bridge between higher education and the evolving demands of the labour market, strengthening both employability outcomes and the adaptability of higher education systems (Eimer & Bohndick, 2023).

Embedding co-creation in assessment design also supports diversity, inclusivity, and cultural responsiveness. It recognises that institutional culture and industry norms shape how competencies are valued and assessed, requiring higher education to bridge academic and professional cultural expectations (Healey et al., 2014; Hofstede et al., 2010).

Taken together, these mechanisms motivate the integration of AI to deliver timely feedback and authentic performance evidence at scale, which the subsequent section synthesises.

Artificial Intelligence in Assessment: Innovation, Ethics, and Organisational Culture

A synthesis is developed by examining how AI extends aligned, co-created assessments via adaptive feedback and analytics, with ethical safeguards maintained. Recent advancements in artificial intelligence are transforming higher education assessment by offering immediate, adaptive, and highly personalized feedback. The design of contemporary assessment models must begin with clarity about the learning outcomes they seek to achieve. AI-powered systems using natural language processing and predictive analytics have demonstrated their effectiveness in delivering tailored feedback that supports diverse learning needs across multiple disciplines (Luo et al., 2025; Merino-Campos, 2025).

These tools have been applied successfully in fields such as medical education, where AI aids in simulating clinical scenarios and offering instant guidance; in engineering, where student agency is fostered through interactive adaptive systems; and in the humanities, where machine-mediated feedback promotes deeper reflection and engagement (Darvishi et al., 2024; Gao et al., 2024; Khong & Tanner, 2024). The shift from static assessment models to AI-augmented feedback loops enhances student learning outcomes and increases engagement, with systematic reviews highlighting substantial gains in motivation, metacognitive skills, and emotional support (Bond et al., 2024; Crompton & Burke, 2023; Weidlich, 2025).

Beyond student benefits, AI-enabled feedback loops create reciprocal value for educators and industry stakeholders. For educators, AI analytics provide granular insights into learning trajectories, enabling data-driven adjustments to curriculum and teaching strategies in real time (Zawacki-Richter et al., 2019). For industry partners, aggregated performance data, when ethically managed, offers valuable intelligence on graduate skill readiness, aligning recruitment and training initiatives with evolving workplace demands (Ferreira-Meyers, 2025). These feedback cycles strengthen the partnership between higher education and industry, ensuring curricula remain relevant while fostering sustained collaboration.

Ethical AI integration is essential to realising these benefits without compromising trust. Studies underscore the need for transparent algorithmic design, mitigation of bias, and clear communication of AI's role in assessment (Holmes et al., 2023; Webb et al., 2023). Responsible governance frameworks recommend stakeholder co-design of AI tools, regular audits of algorithmic fairness, and the inclusion of ethical AI literacy within faculty and student development programmes (Nazaretsky et al., 2025). Such measures ensure that AI adoption aligns with both institutional values and regulatory requirements, particularly around data privacy and equitable learning opportunities.

Emerging frameworks offer practical roadmaps for embedding AI into assessment design, emphasising transparency, accountability, and ethical governance—key considerations for scalable implementation (Bulut et al., 2024; Ilieva, 2025; Sajja et al., 2024). Empirical research shows that AI-generated adaptive feedback improves performance and interest in technical subjects, especially compared to traditional static feedback approaches (Bauer et al., 2025). Broader investigations demonstrate how combining AI and learning analytics supports data-driven pedagogical decisions and personalised interventions (Banihashem et al., 2022; Caspari-Sadeghi, 2022; Sajja et al., 2024).

The successful adoption of AI-enabled assessment requires not only robust technical infrastructure but also a supportive organisational culture that fosters trust, openness to innovation, and shared ethical commitments across academic and industry stakeholders (Holmes et al., 2023; Zawacki-Richter et al., 2019). Cultural readiness has been identified as a critical enabler in the diffusion of educational technologies, influencing not only the willingness of educators and students to engage with AI-driven tools but also the depth and sustainability of their integration (Kirkwood & Price, 2014; Teräs, 2022). In higher education, cultures that embrace experimentation, interdisciplinary collaboration, and reflective practice are more likely to leverage AI in ways that enhance learning outcomes while maintaining academic integrity (Nazaretsky et al., 2025; Webb et al., 2023). From an industry partnership perspective, a culture of co-creation and mutual respect ensures that AI-enabled assessment innovations remain aligned with real-world professional demands and ethical standards (Ankrah & AL-Tabbaa, 2015; Perkmann et al., 2013). This alignment extends to embedding shared values around data privacy, fairness, and transparency, which are increasingly seen as prerequisites for stakeholder buy-in and long-term collaboration (Fu & Weng, 2024; Holmes et al., 2023; Sajja et al., 2024). Without these cultural foundations, even the most advanced AI systems risk underutilisation or rejection, underscoring the need for institutions to invest as much in cultivating adaptive, ethically grounded cultures as in acquiring technological capabilities.

Altogether, the literature underscores AI's potential to address longstanding limitations of traditional assessment. When implemented ethically, it enables tailored, scalable feedback, supporting student autonomy and engagement while delivering actionable insights for educators and industry. Realising this potential depends on cultivating an organisational culture that values trust, openness to innovation, and shared ethical responsibility among academic and industry partners. This foundation strengthens the alignment between innovative inputs and effective assessment outcomes, positioning AI as both a pedagogical tool and a strategic driver of higher education–industry synergy.

Methods

Research Design

This study adopts a Design Science Research (DSR) approach to develop and validate the AI-Enabled Industry-Collaborative Assessment Model (AI-ICAM). DSR is particularly suited for creating and evaluating artefacts that solve identified problems within a practical context (Hevner et al., 2004). In line with DSR principles, the research process followed an iterative cycle of problem identification, artefact development, evaluation, and refinement.

The design process was grounded in Constructive Alignment Theory (Biggs & Tang, 2011), principles of knowledge co-creation between higher education and industry (Ankrah & AL-

Tabbaa, 2015; Perkmann et al., 2013), and frameworks for ethical AI integration in education (Holmes et al., 2023; Webb et al., 2023). The model was also informed by the literature on employability and sustainable development in higher education (Ho et al., 2023; Leal Filho et al., 2019).

Table 1 summarises the AI-ICAM's core components, their theoretical foundations, practical objectives, and supporting literature. This mapping establishes conceptual clarity and links the model directly to peer-reviewed evidence.

Table 1
Alignment of AI-ICAM Components With Research Foundations and Practical Objectives

Framework Component	Theoretical Foundation	Practical Objective	Supporting Literature
Constructive Alignment	Biggs and Tang's (2011) alignment theory; Boud & Molloy (2013) on assessment as learning	Ensure coherent link between learning outcomes, teaching, and assessment to promote deep learning	Biggs and Tang (2011); Boud and Molloy (2013); Perkmann et al. (2013)
Industry Co-Creation	Stakeholder theory in higher education–industry collaboration (Ankrah & AL-Tabbaa, 2015)	Integrate authentic, workplace-relevant tasks into assessment	Ho et al. (2023); Huang (2025); Jackson (2016)
Ethical AI Integration	Responsible AI frameworks (Holmes et al., 2023; Webb et al., 2023)	Maintain transparency, fairness, and accountability in AI-enabled assessment	Nazaretsky et al. (2025); Zawacki-Richter et al. (2019)
AI-Driven Feedback Loops	Feedback literacy and SEFL model (Crompton & Burke, 2023; Kovari, 2025)	Provide real-time, personalised feedback that benefits both students and educators	Darvishi et al. (2024); Gao et al. (2024); Luo et al. (2025)
SDG Alignment	Education for Sustainable Development (Findler et al., 2019; Leal Filho et al., 2019)	Equip graduates with sustainability competencies and global problem-solving skills	Eimer and Bohndick, (2023); Pless et al. (2012); Zainudden et al. (2022)

Methodological Steps

Following DSR guidelines, the development of the AI-ICAM proceeded through six interconnected phases:

1. **Problem Identification**. A systematic literature review and stakeholder needs analysis identified persistent gaps in higher education assessment, including misalignment with professional demands, limited use of authentic assessment tasks, and underutilisation of AI in feedback provision (Brown, 2022; Parmigiani et al., 2024; Whittaker, 2016).
2. **Objective Definition**. Drawing on sustainability and employability frameworks (Ho et al., 2023; Leal Filho et al., 2019), the objectives were defined as:
    (a) align assessment with global and professional competencies;
    (b) integrate industry collaboration into assessment design; and
    (c) implement ethical, AI-enabled adaptive feedback systems.
3. **Framework Design**. Using constructive alignment as the organising principle, assessment tasks, learning activities, and outcomes were mapped to industry-validated competencies, SDGs, and ethical AI standards.

4. **Integration of AI Tools**. AI applications were selected for their capacity to provide real-time, personalised feedback, facilitate learning analytics, and scale to large cohorts. This selection was guided by current empirical findings on AI in higher education assessment (Bulut et al., 2024; Luo et al., 2025).
5. **Validation with Stakeholders**. The model was piloted through three case studies in the School of Business. These case studies provided evidence on the AI-ICAM's practical applicability, highlighting curriculum innovation, improvements in feedback quality, and enhanced graduate employability outcomes.
6. **Evaluation and Refinement**. Data from the case studies (student performance analytics, industry partner feedback on graduate skills, and curriculum documentation) informed iterative refinements to the model.

Table 2 outlines these methodological steps, detailing the description, key activities, outputs, and supporting literature for each phase.

Table 2
Methodological Steps for Developing the AI-ICAM Framework Using a Design Science Approach

Phase	Purpose	Key Activities	Outputs
1. Problem Identification	Identify persistent challenges in higher education assessment	Systematic literature review; stakeholder needs analysis from policy documents and institutional reports	Evidence base highlighting misalignment with professional demands, lack of authentic tasks, limited AI use
2. Objective Definition	Establish strategic and pedagogical aims for AI-ICAM	Map goals to sustainability, employability, and industry collaboration frameworks	Defined objectives for alignment with competencies, integration of industry, and ethical AI feedback
3. Framework Design	Develop structure for AI-ICAM grounded in theory	Apply constructive alignment principles to link learning outcomes, activities, and assessments	Drafted model with mapped competencies to SDGs, industry standards, and ethical AI principles
4. Integration of AI Tools	Select and embed AI capabilities	Evaluate AI tools for feedback speed, adaptivity, scalability, and ethical compliance	Integrated AI applications providing real-time personalised feedback and learning analytics
5. Validation via Case Studies	Test AI-ICAM in authentic educational contexts	Implement three case studies within the School of Business, each involving collaboration with different industry partners.	Evidence of curriculum innovation, enhanced feedback, improved graduate employability
6. Evaluation and Refinement	Assess effectiveness and refine model	Analyse case study results; align outcomes with objectives; update model components	Revised AI-ICAM with enhanced alignment, industry relevance, and ethical safeguards

Data Sources and Stakeholders

To support a robust, multi-perspective validation of the AI-ICAM model, data were drawn from three principal stakeholder groups. Academic staff provided evaluative reflections on pedagogical alignment, constructive alignment with intended learning outcomes, and the feasibility of integrating AI-enabled assessment within existing curricula. Industry partners contributed feedback on professional relevance, graduate employability, and the authenticity of assessment tasks, with insights drawn from documented site visit reports and existing consultation summaries. Student perspectives were captured through course evaluation data and reflective submissions, focusing on their experiences of feedback quality, inclusivity, and engagement with the AI-supported assessment processes.

Ethical Considerations

This study did not involve the collection of new human participant data; all evidence was derived from secondary institutional sources. As this study relied exclusively on secondary data, case study documentation, and reflective accounts from participating stakeholders, no primary data involving identifiable personal information were collected. All stakeholder feedback, including insights from industry site visits and academic reflections, was drawn from pre-existing institutional records and anonymised course evaluations in compliance with university data governance policies. The analysis adhered to the ethical principles of transparency, confidentiality, and responsible use of stakeholder contributions. Where industry partner perspectives were incorporated, care was taken to avoid disclosure of proprietary or commercially sensitive information. The integration of AI tools into the assessment model was guided by responsible AI frameworks to ensure transparency, fairness, and the minimisation of bias, aligning with established ethical standards in educational research.

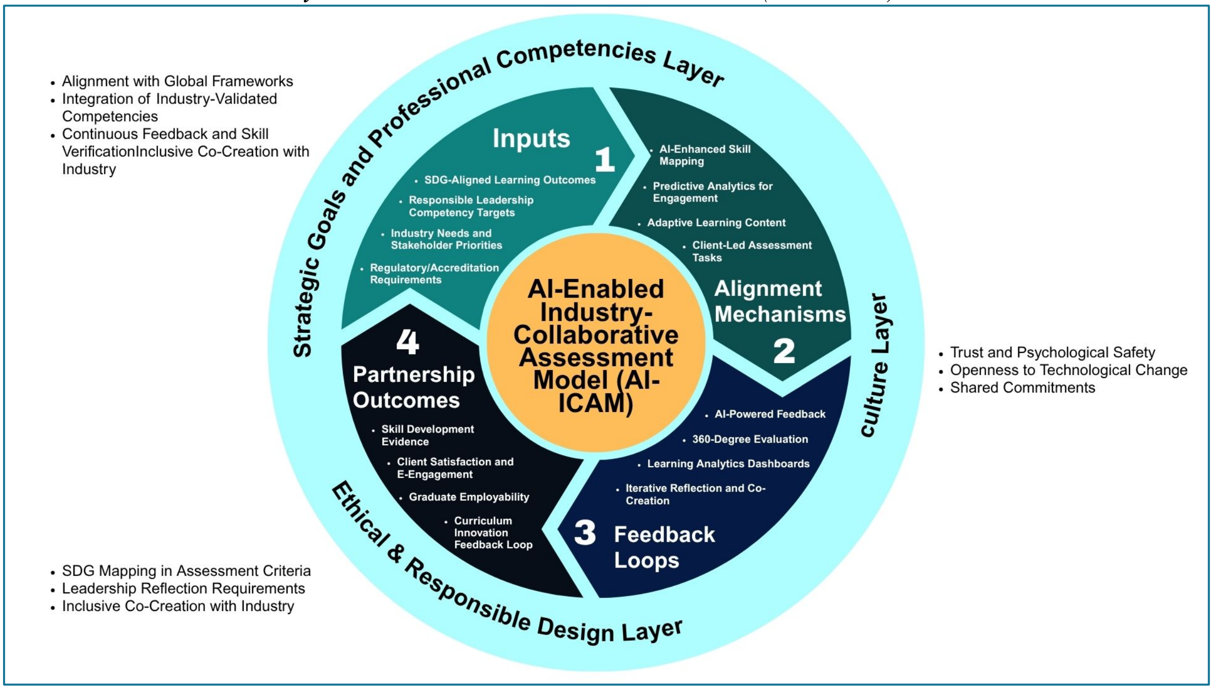
The AI-ICAM Model

Figure 1 shows the AI-Enabled Industry-Collaborative Assessment Model (AI-ICAM), developed through a six-phase Design Science Research process. The model combines four elements: constructive alignment, industry co-creation, ethical AI integration, and AI-driven feedback loops within a culture of innovation. This structure links global and professional competency goals, including the United Nations Sustainable Development Goals, with authentic, industry-informed assessment.

Inputs include SDG-aligned learning outcomes, responsible leadership competencies, and industry priorities. These inform Alignment Mechanisms such as AI-enhanced skill mapping, adaptive content, and predictive analytics. Feedback Loops, powered by AI analytics and stakeholder evaluation, drive continuous refinement. Partnership Outcomes such as curriculum innovation, graduate employability, and evidence of skill development maintain relevance for academia and industry.

Grounded in a culture of trust, openness, and ethical responsibility, AI-ICAM ensures transparent, fair, and context-responsive AI integration. It provides a scalable, adaptable framework for transforming assessment into a collaborative process bridging higher education and the future workplace.

Figure 1
The AI-Enabled Industry-Collaborative Assessment Model (AI-ICAM)



Results

Guided by AI-ICAM (Figure 1), the following cases illustrate how collaboration with industry partners and AI-supported feedback altered assessment design, delivery, and evidencing of outcomes.

Case Study 1: Sustainability and Digital Marketing in Practice Module (Live Client: IGS)

This case study applied the AI-ICAM framework within a undergraduate digital marketing module in collaboration with Intelligent Growth Solutions (IGS), a sustainable agriculture technology company. Assessment centred on a live client consultancy report, requiring students to design sustainability-focused digital marketing strategies aligned with the UN Sustainable Development Goals (SDGs).

Students were encouraged to incorporate AI tools into their creative process, including generating mock-up visuals for campaigns and experimenting with AI-generated music to test potential emotional and branding effects. These AI applications supported the development of more engaging and innovative client deliverables. Industry partner feedback highlighted the originality of student outputs and the alignment with IGS's sustainability messaging.

The organisational culture at IGS, rooted in sustainability-driven innovation, directly influenced students' approach to campaign development. This cultural emphasis encouraged solutions that went beyond conventional marketing tactics to incorporate ecological values and long-term social impact.

The live consultancy assessment retained its summative brief but introduced two AI-supported formative checkpoints: (1) early concept scoping with AI-generated mock-ups and tutor feedback, and (2) mid-cycle alignment to SDG targets using an AI-assisted checklist.

This shifted time on task from final-week polishing to earlier iteration, improved coherence with sustainability criteria in the rubric, and produced client-ready assets that evidenced alignment.

While AI was not yet used for data analytics or campaign simulation in this iteration, academic staff identified this as a valuable opportunity for future development. The proposed next step involves integrating AI-driven analytics for formative testing of campaign concepts, enabling a more evidence-based iteration process prior to final client delivery.

Case Study 2: Biz-a-thon Event With NCR Atleos

The Biz-a-thon, an intensive innovation sprint, was co-designed with NCR Atleos to replicate real-world product development and sustainability challenges in the financial technology sector. Multidisciplinary student teams proposed sustainable digital solutions for self-service banking, aligning with NCR Atleos' corporate strategy and the UN Sustainable Development Goals (SDGs), directly reflecting the SDG alignment and industry co-creation components of AI-ICAM.

In preparatory workshops and during the event, students were introduced to AI tools and example prompts to support rapid ideation and creative output. Many teams used AI to generate campaign visuals, promotional mock-ups, and short-form videos, applying the AI-driven feedback loop principle by iterating concepts quickly and enhancing the persuasiveness of final presentations. This rapid prototyping enabled more time for problem analysis, solution refinement, and integration of sustainability considerations, strengthening the constructive alignment between assessment criteria and deliverables.

Industry evaluators praised the creativity and polish of outputs, noting that AI-assisted production elevated presentation standards under tight time constraints. While AI was not yet applied for advanced functions such as feasibility analysis or impact modelling, its role in supporting communication design, collaborative workflows, and professional delivery was clear.

The sprint combined a timed presentation with an evidence pack, using AI for prototyping and storyboard generation to externalise ideas early and apply rubric indicators on feasibility and sustainability during iteration. This improved clarity and made feedback traceable to criteria rather than subjective impressions.

The Biz-a-thon reflected NCR Atleos' fast-paced, collaborative culture, rewarding agility, creativity, and calculated risk-taking. Planned future iterations will embed AI more deeply into assessment, incorporating real-time feasibility evaluation, sustainability impact modelling, and adaptive feedback to fully operationalise the feedback loop and ethical AI integration elements of AI-ICAM.

Case Study 3: Conversations With Industry Leaders Podcast Integration

As part of the Search Marketing and Sustainability and Digital Marketing in Practice modules, the Conversations with Industry Leaders podcast was created and embedded as formative learning resources. The curated episodes featured in-depth discussions with recognised experts, including a leading search marketing strategist and senior executives from NCR

Atleos, on the transformative impact of artificial intelligence in digital marketing, sustainability innovation, and corporate responsibility.

This activity aligned with AI-ICAM's industry co-creation and ethical AI integration elements by providing authentic, current perspectives that directly supported learning outcomes on emerging technologies, ethical leadership, and sustainable business practice. The flexible, accessible podcast format promoted inclusive learning and extended student engagement with real-world expertise beyond the classroom, encouraging varied learning styles.

Engagement metrics and informal student feedback showed increased interest in industry trends and greater application of professional insights in coursework. Staff observed these discussions enhanced students' strategic thinking in AI-assisted tasks, such as audience targeting, sustainability messaging, and campaign optimisation, linking to the model's feedback loop principle by influencing decision-making in related assessments.

The episodes also exposed students to varied organisational cultures in digital adoption, sustainability integration, and AI ethics. This reinforced AI-ICAM's emphasis on cultural context as a driver of effective assessment innovation, showing how organisational values shape the implementation of emerging technologies and sustainability strategies.

While AI tools were not directly embedded into the podcast activity, this case demonstrates how industry-embedded multimedia content can indirectly strengthen AI literacy and integration across projects. Future iterations could incorporate targeted AI tools for reflective analysis, enabling students to draw stronger connections between expert insights and their own project work, further operationalising AI-ICAM's feedback and alignment mechanisms.

Cross-Case Analysis

Across all three cases, the integration of AI within the AI-ICAM framework consistently enhanced creativity, time-efficiency, and the professional quality of student outputs. In Case Studies 1 and 2, AI was applied directly to content creation, enabling rapid production of high-quality visuals, multimedia assets, and presentation materials that elevated client deliverables and industry pitches. In contrast, Case Study 3 employed indirect integration, where exposure to industry-led discussions on AI and sustainability informed students' strategic thinking and shaped application of AI tools in assessments. Variations in AI use highlight differing levels of technological maturity within assessment contexts—from creative augmentation in design-focused tasks to strategic influence in knowledge application activities. Collectively, these findings indicate that deeper, more systematic embedding of AI within formative and summative assessment processes could strengthen the adaptive feedback loops central to the AI-ICAM model, particularly through real-time feasibility testing, sustainability impact modelling, and expanded ethical AI literacy.

A synthesis of results across the three case studies is presented in Table 3, highlighting common themes, variations in AI integration, and implications for further refinement of the AI-ICAM framework.

Table 3
Summary of Case Study Findings and AI-ICAM Implications

Case Study	Context & Stakeholders	AI Integration Type	Key Outcomes	Implications for AI-ICAM Refinement	Cultural & Strategic Considerations
Sustainability and Digital Marketing in Practice (IGS)	Postgraduate digital marketing module; live client consultancy with sustainable agriculture technology company	**Direct:** AI used for creative outputs (mock-up visuals, AI-generated music)	Enhanced creativity and originality; stronger alignment with client sustainability messaging	Integrate AI-driven analytics for formative campaign testing to support evidence-based iteration	Demonstrated openness from industry partner to student-led innovation; fostered cross-disciplinary dialogue on sustainability culture
Biz-a-thon with NCR Atleos	Multidisciplinary innovation sprint with financial technology industry partner	**Direct:** AI for rapid production of visuals, videos, and slide design in time-limited environment	Increased time-efficiency; improved presentation polish; industry recognition of professional quality	Extend AI use to real-time feasibility testing, sustainability impact modelling, and adaptive feedback	Culture of high-paced collaboration and innovation readiness facilitated rapid adoption of AI tools
Conversations with Industry Leaders Podcast	Search Marketing and Digital Strategy modules; curated industry expert episodes on AI and sustainability	**Indirect:** Industry insights informed student strategic thinking and application of AI in other tasks	Increased engagement with emerging trends; improved integration of professional perspectives in coursework	Develop structured reflective tasks linking industry insights to explicit AI use in assessments	Supported creation of a learning culture valuing continuous professional engagement and cross-sector knowledge sharing

Discussion

Interpretation of Key Findings

The study specifies three assessment levers through which AI-enabled industry collaboration operates: design (earlier, rubric-aligned iteration with authentic constraints), delivery (timely, AI-assisted formative checkpoints that rebalance time on task), and evidence (traceable artefacts and feedback linking explicitly to professional standards and SDG targets). Articulating these levers clarifies not only that collaboration matters but how it reconfigures assessment practice.

The findings from the three case studies collectively demonstrate that the AI-Enabled Industry-Collaborative Assessment Model (AI-ICAM) is capable of enhancing the quality, relevance, and inclusivity of assessment in higher education. Across contexts, AI contributed to creativity, time-efficiency, and professional output quality, validating its role as both a pedagogical and strategic enabler. Direct AI integration, as seen in the Sustainability and

Digital Marketing module (Case Study 1) and the Biz-a-thon event (Case Study 2), enabled students to rapidly prototype communication assets, refine presentation materials, and explore novel creative strategies. In contrast, the Conversations with Industry Leaders podcast (Case Study 3) illustrated that even indirect AI exposure, when mediated through authentic industry discourse, can influence student thinking and stimulate adoption of AI tools in other projects.

These variations underscore a central premise of AI-ICAM: the value of AI in assessment is not confined to direct application during task completion but extends to shaping students' strategic thinking, digital literacy, and adaptability. A critical enabling factor across all three cases was the shared culture of innovation fostered between academic staff, students, and industry partners. This culture, which is characterised by trust, openness to experimentation, and receptiveness to emerging technologies, appeared to accelerate AI adoption and deepen its pedagogical impact (Holmes et al., 2023; Webb et al., 2023; Zawacki-Richter et al., 2019). Moreover, the integration of industry collaboration across all cases reinforced assessment authenticity, bridging the gap between academic requirements and professional expectations while embedding sector-specific cultural norms into the learning process (Ho et al., 2023; Jackson, 2016; Perkmann et al., 2013).

Integrating AI-ICAM Into Broader Practice

Adopting the AI-Enabled Industry-Collaborative Assessment Model (AI-ICAM) at scale requires aligning institutional priorities, curriculum design, and industry engagement. The model's Inputs, which include SDG-aligned learning outcomes, responsible leadership competencies, and industry-validated priorities, provide a foundation for curriculum review. Mapping current programmes against these inputs can reveal gaps in global alignment and accreditation readiness.

Alignment Mechanisms such as AI-enhanced skill mapping, predictive analytics, and adaptive learning content offer practical tools for enhancing relevance and inclusivity. To extend their impact, these mechanisms should be integrated into institutional systems and supported by staff training to help educators interpret and act on AI-driven insights.

The model's Feedback Loops, including AI-powered feedback, 360-degree evaluation, and iterative co-creation, support continuous refinement of assessment. Applied across disciplines, they allow educators and industry partners to respond rapidly to learner needs while maintaining ethical and responsible AI use.

Partnership Outcomes, which include skill development evidence, graduate employability, and curriculum innovation, signal the importance of sustained collaboration. Embedding industry engagement as a standard assessment practice ensures outputs remain relevant to evolving professional contexts.

The outer layers of AI-ICAM emphasise three conditions for successful integration: strategic alignment with global frameworks and professional competencies, embedding ethical and responsible design principles, and fostering a culture of trust, openness, and shared commitment to innovation. Without these, technical components risk being underused or resisted.

By linking each adoption step to both structural components and cultural enablers, AI-ICAM provides a transferable framework for transforming assessment into a dynamic, collaborative process that bridges academic learning with the demands of the future workplace.

Conclusion and Implications

This study set out to investigate how artificial intelligence can be leveraged to design assessment in higher education that is inclusive, adaptive, and authentically connected to industry collaboration. The AI-Enabled Industry-Collaborative Assessment Model (AI-ICAM) addresses this aim by integrating AI capabilities with constructive alignment, co-creation with industry partners, and a culture of innovation. Across three case studies, both direct and indirect AI integration enhanced creativity, time efficiency, and professional presentation quality, while also strengthening student engagement with sustainability and employability goals.

Theoretically, AI-ICAM extends assessment design literature by explicitly incorporating culture as a structural layer, positioning organisational trust, openness to experimentation, and alignment of ethical values as central enablers of AI adoption. This cultural dimension advances constructive alignment theory by recognising the socio-cultural context as a driver of assessment effectiveness.

Practically, the findings highlight three strategic priorities for higher education institutions: (1) align investment in AI infrastructure with strategies to cultivate an innovation-oriented and ethically grounded culture, (2) embed iterative feedback loops supported by AI analytics to refine outputs in real time, and (3) formalise sustained industry collaboration as a mechanism for ensuring authentic, current, and sector-relevant assessment practices.

The AI-ICAM offers a scalable, adaptable template for disciplines and sectors seeking to integrate AI-enabled assessment. Limitations include the focus on three case studies within specific programme contexts, suggesting the need for broader, cross-disciplinary validation. Future research should examine longitudinal impacts on graduate employability and test AI-ICAM in diverse cultural and institutional settings to explore its adaptability and boundary conditions. With thoughtful implementation, AI-ICAM can transform assessment into a dynamic, collaborative process that bridges higher education with the evolving demands of the future workplace.

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