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Artificial Intelligence in Higher Education Assessment: International Experience and Implications for Vietnam

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ABSTRACT: Artificial intelligence is expanding the capacity for scoring, feedback, learning analytics, and early warning in higher education, while creating risks concerning bias, privacy, and accountability. This review addresses three questions: how AI is applied and what value it offers; which implementation and governance lessons emerge from the United States, Europe, Singapore, Korea, and OECD countries; and what opportunities and challenges Vietnam faces. The synthesis indicates that benefits depend on fit-for-purpose data, tool validation, transparency, and meaningful human oversight. The article proposes a ten-step implementation framework and a four-stage roadmap that prioritise limited pilots, appeal mechanisms, and impact evaluation before scaling. AI should support, rather than replace, academic judgement and institutional responsibility.

KEYWORDS: assessment for learning, learning analytics, algorithmic governance, human oversight, digital education transformation.

1. INTRODUCTION

Assessment in higher education determines the extent to which learning outcomes have been achieved and provides evidence for improving teaching and assuring quality. Within assessment for learning, evidence helps identify the gap between current performance and intended goals so that appropriate feedback can be provided (Black & Wiliam, 2009). Learning objectives, tasks, rubrics and academic decisions must therefore be aligned. Digitalization extends the evidence base beyond grades to include progress, feedback and interaction traces. Artificial intelligence (AI) and learning analytics can support scoring, feedback and the prediction of academic risks. However, these outputs are valuable only when translated into pedagogical action (Ifenthaler & Yau, 2020) and must not replace professional human judgement (OECD, 2021). Although AI can shorten processing time, it also poses risks of bias, data intrusion and diminished accountability. International guidance emphasizes fairness, data security and human decision-making authority (European Commission, 2022; UNESCO, 2023; U.S. Department of Education, 2023).

In Vietnam, digital transformation initiatives and data protection regulations have established a general foundation, but a dedicated process for AI-assisted assessment has not yet been established (Government of Vietnam, 2023; Prime Minister of Vietnam, 2020). This study examines applications, international experience, opportunities and challenges, and proposes an implementation framework.

2. RESEARCH CONTENT

2.1. Theoretical background and review method

Assessment of learning is the process of collecting, interpreting and using evidence to determine the achievement of objectives or learning outcomes. Summative assessment confirms achievement at a particular point, whereas formative assessment supports improvement while learning is still taking place. Feedback is meaningful when it helps learners understand the goal, identify gaps and select their next steps (Black & Wiliam, 2009). Thus, the speed offered by AI cannot substitute for sound assessment criteria and opportunities for revision.

AI in education encompasses methods for pattern recognition, prediction, content generation and action recommendations. Learning analytics focuses on data about learners and their environments to understand, support and optimize learning. In assessment, AI can match responses against rubrics, classify answers, synthesize data and generate feedback. Tools should be selected only after learning outcomes have been defined; otherwise, prioritizing readily measurable features may distort the competencies being assessed.

The degree of automation should be proportionate to the consequences of a decision. Practice tasks may allow greater automation, whereas final grades, competency certification and academic decisions require independent review. A human-in-the-loop approach requires qualified professionals to understand system limitations, have genuine authority to intervene and remain ultimately accountable, rather than merely endorsing machine-generated outputs (U.S. Department of Education, 2023).

This review coded the literature by application functions, value, risks, human roles and control mechanisms; compared international cases; and synthesized policy implications. Sources were retained where their publication provenance was credible, bibliographic information was verifiable and the content was directly relevant. Unverifiable system names, programme names and quantitative results were excluded.

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2.2. AI Applications, benefits and risks in learning assessment

Automated scoring is best suited to closed questions, short responses or written tasks with stable rubrics. Systems can increase speed and consistency, but may overlook context, original ideas or expressions outside anticipated patterns. Their output should therefore be used for screening, recommendations or preliminary marking; complex assessments require lecturer review of substance and creativity. AI can also provide immediate feedback, identify errors, suggest next steps and generate guiding questions. Its value lies in increasing opportunities for revision, not in doing learners' cognitive work for them. Singapore has integrated feedback assistants and response analysis into learning platforms while allowing teachers to adjust system-generated content (Ministry of Education, Singapore, 2025).

Learning analytics combines progress, interaction and performance data to support early warning. Predictions are useful only when connected to counselling, supplementary resources or task adjustments; simply labelling students as at risk has limited educational value (Ifenthaler & Yau, 2020). Probabilities must not be treated as certainty because they can reinforce stereotypes. Tools detecting anomalies, text similarity or changes in writing style provide signals for investigation rather than proof. False positives may arise in short assignments, work by second-language learners or inconsistent writing styles. Fair procedures must distinguish technical indicators from evidence, permit explanations and prohibit findings of misconduct based solely on automated signals. AI can also support competency assessment through simulations, process analysis and adaptive task difficulty, but this requires evidence of measurement validity, comparability and clearly limited data uses. UNESCO (2023) recommends evaluating tools against educational goals, data protection and learner autonomy. Table 1 demonstrates the need for validation and oversight across all application categories.

Table 1. Application categories of ai in learning assessment

Application	Core function	Value for lecturers and learners	Risks or limitations	Required controls
Automated scoring	Match answers and rubrics; suggest scores or categories	Faster processing; consistency for structured tasks	May miss novel ideas, context or unanticipated wording	Sample marking; comparison with lecturers; discrepancy reviews
Immediate feedback	Identify errors; suggest next steps; pose guiding questions	More revision cycles; support self-regulation	Generic or inaccurate feedback; replacement of learner thinking	Clear rubrics; teacher adjustments; learner right to question
Learning analytics	Aggregate progress, engagement and results	Identify support needs; improve courses	Behavioral traces do not fully capture learning	Purpose limitation; data quality checks
Early warning	Predict delayed progress or non-completion	Timely intervention; targeted support	Labelling and bias; confusion of correlation with causation	Treat predictions as alerts; counselling and reassessment
Anomaly detection	Identify similarity, access patterns or unusual changes	Support academic integrity investigations	False positives; difficulty proving misconduct	No automated findings; explanation and appeals process
Competency assessment	Analyze outputs, processes or simulations	Richer evidence; assessment of complex skills	Measurement validity challenges; costly validation	Explicit competency model; expert review; reliability testing
Adaptive assessment	Adjust questions, difficulty or resources	Level-appropriate tasks; stronger support	Reduced comparability; unequal learning paths	Standardized elements; fairness monitoring across groups

Source: Compiled by the author from Black and Wiliam (2009), Ifenthaler and Yau (2020), OECD (2021), UNESCO (2023), and U.S. Department of Education (2023).

2.3. International experience in AI-assisted assessment

In the United States, assessment technologies are developed through the involvement of educational institutions, testing organizations and industry. Guidance from the U.S. Department of Education (2023) calls for educational objectives to take precedence over technical capabilities, for educators to participate in design and for humans to remain within the decision-making loop. For high-stakes assessment, institutions must validate the tools, disclose their scope of use and retain responsibility instead of transferring it to vendors.

Europe adopts a rights-based and risk-oriented approach to AI governance. European Commission guidance (2022) requires educational users to examine necessity, transparency, fairness, privacy and effects on learner autonomy before deploying tools. Practical measures include documentation of data flows, explanation of key operating logic and limitations, and the right to request human review.

Singapore stands out for its coordination of platforms, tools, data, training and ethical governance. Its AI-in-education framework emphasizes agency, inclusion, fairness and safety. Feedback tools, short-answer marking and analytics allow teachers to review and adjust outputs (Ministry of Education, Singapore, 2025). This experience offers lessons for Vietnamese universities regarding shared platforms, vetted tools and centralized professional support.

The Republic of Korea announced an AI Digital Textbook plan in 2023 combining adaptive content, learning-progress data, teacher training and tool evaluation (Ministry of Education, Republic of Korea, 2023). This experience primarily concerns school education and should

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not be represented as evidence of effectiveness in universities. Transferable lessons concern phased implementation, platform standards and clear legal status for digital tools.

OECD countries differ in governance arrangements but are integrating AI, learning analytics and learning management systems. OECD (2021) describes a hybrid human–machine system and warns about digital divides, interoperability and vendor dependence. Public–private partnerships should therefore address data ownership, portability, auditing and contract termination. Across contexts, educational goals should lead technology choices; lecturers should retain decision-making authority; data collection should be minimized; tools should be tested with relevant learner groups; and learners should receive notice and have access to an appeal process.

Table 2. Comparison of international experience in AI-assisted assessment

Country/region	Representative uses	Implementation model	Governance principles	Lessons for Vietnam
United States	Assisted scoring, analytics and feedback generation	Institutions and vendors co-develop; context-based validation	Human-in-the-loop; educator participation; trust	Clear institutional accountability; testing before high-stakes decisions
European Union	AI and data for teaching, assessment and learner support	Rights-based, risk-oriented governance	Transparency, fairness, privacy, accountability	Document data flows; notify learners; right to human reconsideration
Singapore	Feedback assistants, response analytics, adaptive learning	Shared platforms; centrally managed tools; teacher adjustment	Agency, inclusion, fairness, safety	Platform standards and professional support; pedagogy-led use
Republic of Korea	AI-enabled digital content, personalization, progress data	National strategy; tool evaluation; teacher training	Quality control; system security; phased rollout	Phased pilots; standards and clear legal status
OECD countries	Integration of AI, analytics and learning management systems	Hybrid human–machine systems; industry partnerships	Fairness, interoperability, impact assessment, vendor governance	Data standardization; portability, audits and exit clauses

Source: Compiled by the author from European Commission (2022), OECD (2021), Ministry of Education, Singapore (2025), Ministry of Education, Republic of Korea (2023), and U.S. Department of Education (2023).

2.4. Opportunities and challenges for Vietnamese higher education

Vietnam's digital transformation, the growing availability of learning management systems and the emphasis on outcome-based assessment create opportunities for AI adoption (Prime Minister of Vietnam, 2020). Appropriate tools could broaden formative assessment, accelerate feedback, support large classes and produce evidence for course improvement. More immediately feasible uses are tasks with explicit criteria, such as progress aggregation, closed-question scoring, error classification and preliminary feedback suggestions.

The first obstacle is uneven infrastructure and data readiness. Many systems operate in isolation; course codes, learning outcomes and rubrics are not consistently standardized; and data are incomplete or difficult to export. Models trained on unrepresentative data may disadvantage disciplines or modes of expression that are underrepresented. Institutions should therefore inventory data, assess quality and remove unnecessary information before implementation.

Another challenge is lecturers' AI competence, assessment literacy and available time for oversight. Professional development should cover measurement validity, ethics, privacy, task design and error handling, not merely software operations. Where reviewers lack authority or time to intervene, human oversight becomes a formality.

Decree No. 13/2023/ND-CP provides a general foundation for personal data protection, but each institution must specify purposes, permissions, retention, incident response and responsibilities (Government of Vietnam, 2023). Vendor contracts should clarify data location, reuse rights, model training, export and obligations upon termination. Policies must also ensure comparable access to devices and accounts and an explanation when AI affects assessment outcomes.

2.5. A proposed framework for AI-assisted assessment in Vietnam

The proposed implementation framework comprises ten steps: (1) define objectives, learning outcomes and the stakes of decisions; (2) standardize data, rubrics and access permissions; (3) select tools based on pedagogical, technical and legal criteria and vendor portability; (4) conduct limited pilots; (5) compare AI outputs with lecturer judgements and test for bias; (6) establish thresholds requiring human review; (7) minimize and encrypt data and retain audit logs; (8) provide notice, feedback and appeals; (9) evaluate quality, fairness, cost and incidents; and (10) revise the process before scaling up.

Figure 1 illustrates the workflow from learning outcomes, assessment tasks, data collection and AI analysis to lecturer verification, feedback, appeals and teaching improvement. AI offers recommendations only; lecturers or academic committees retain final responsibility. This approach is consistent with UNESCO's (2023) human-centered perspective, the U.S. human-in-the-loop model and European ethical guidance.

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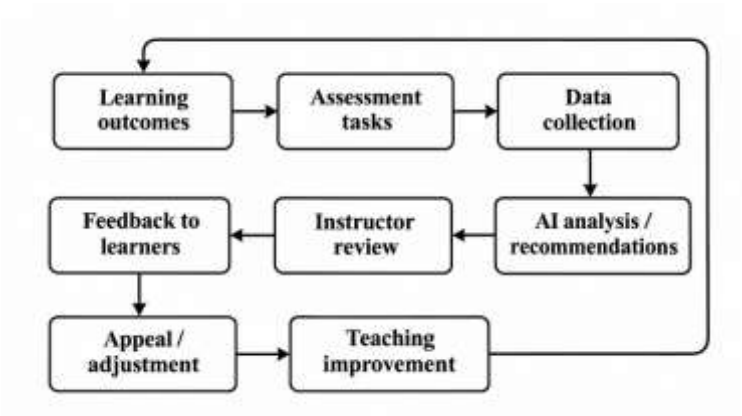

Figure 1. Human-supervised AI-assisted learning assessment model
Source: Proposed by the author based on the reviewed literature.

The roadmap comprises four phases. Phase 1 prepares policies, data and personnel. Phase 2 pilots tools in courses with clear rubrics and low risks. Phase 3 evaluates impact, fairness and costs and refines procedures. Phase 4 scales up cautiously across disciplines, with periodic audits and authority to suspend the system. Material changes to the model, data or vendor should trigger renewed piloting or impact assessment.

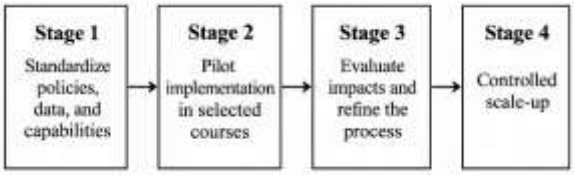

Figure 2. Roadmap for implementing AI in assessment at Vietnamese higher education institutions
Source: Proposed by the author based on the reviewed literature.

3. CONCLUSION AND RECOMMENDATIONS

3.1. Conclusions

Regarding RQ1, AI is applied in scoring, feedback, learning analytics, early warning, anomaly detection, competency assessment and personalization. It can accelerate processing, expand feedback cycles and support data-informed improvement. Limitations include bias, weak explainability, false positives and diminished authenticity. AI therefore does not replace lecturers in designing assessments, interpreting evidence or assuming responsibility for outcomes.

Regarding RQ2, the United States emphasizes educator participation and human-in-the-loop decision-making; Europe prioritizes rights, transparency and data protection; Singapore develops coordinated platforms and support; the Republic of Korea emphasizes strategy, evaluation and phased deployment; and the OECD highlights organizational capabilities and vendor governance. Shared principles include context-specific validation, learner notification, the right to human review and institutional accountability that cannot be delegated to vendors.

Regarding RQ3, Vietnam has opportunities arising from digital transformation and demands for assessment reform, but must address fragmented data, lecturer capacity, privacy, vendor dependence and unequal access. This review contributes a synthesis of international experience and proposes a ten-step framework and a four-phase roadmap. Its limitations are reliance on published materials, differences among education systems and rapid technological change. The proposals require validation through practical pilots.

3.2. Recommendations

Regulatory authorities should issue risk-tiered guidance for applications, minimum requirements for notification, validation, traceability, appeals and accountability, as well as data standards, tool evaluation criteria and mechanisms for sharing pilot findings.

Higher education institutions should establish interdisciplinary governance teams and document each tool's purpose, datasets, test results and shutdown plan. Pilots should begin with voluntary, low-risk courses. Lecturers should design rubrics before selecting tools, check sample outputs and avoid treating any single automated indicator as sufficient proof of misconduct.

Vendors should permit audits, data export and deletion; notify institutions of model changes; and refrain from using student submissions for training beyond agreed purposes. Future research should measure AI–lecturer agreement across disciplines, impacts on disadvantaged groups, total lifecycle costs and the effectiveness of explanation and appeal mechanisms.

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