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Chapter 19: Online Assessment Practices and Student Learning Outcomes in Higher Education

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Abstract— Online assessment has shifted from an emergency substitute for conventional examinations to a persistent component of higher education assessment systems. However, evidence remains fragmented regarding which specific characteristics of digital assessment produce measurable improvements in student learning rather than merely improving administrative efficiency. This study examines online assessment as a multidimensional instructional process involving assessment authenticity, feedback latency, adaptive task design, learner interaction, and technology-supported academic integrity. A central research gap is identified in the limited empirical integration of these dimensions within a single explanatory framework linking assessment practices with cognitive achievement, engagement, knowledge retention, and self-regulated learning. The proposed study therefore develops an Online Assessment Learning Effectiveness Framework that distinguishes between assessment delivery technology and the pedagogical quality of assessment design. It further investigates whether rapid formative feedback and authentic, higher-order assessment activities mediate the relationship between digital assessment practices and student achievement. The framework also incorporates emerging artificial-intelligence-supported assessment practices while recognizing contemporary concerns regarding generative AI, validity, fairness, and academic integrity.

Keywords — Online assessment, higher education, formative feedback, learning outcomes, artificial intelligence, assessment authenticity

Introduction

Digital transformation has altered the relationship between instruction, assessment, feedback, and student participation in higher education. Learning management systems, automated quizzes, electronic portfolios, remote examinations, peer-assessment platforms, simulation-based tasks, and AI-supported feedback systems increasingly enable assessment activities to occur continuously rather than at isolated examination points. Consequently, online assessment is no longer adequately understood as the digital reproduction of a paper-based test. It increasingly represents an integrated learning environment in which evidence about student understanding can be collected, interpreted, and returned to learners throughout the instructional process.

The rapid expansion of digitally mediated higher education following the COVID-19 period accelerated institutional experience with online assessment. Yet the normalization of digital assessment has generated a more demanding question

than whether examinations can technically be conducted online. Universities must now determine which forms of online assessment actually improve learning. This distinction is important because an assessment system can be technologically efficient while remaining pedagogically weak. Automated administration, rapid marking, remote accessibility, and centralized data management may reduce operational burden without necessarily improving conceptual understanding, knowledge transfer, or students' ability to regulate their own learning.

Existing research indicates that digital environments can support diverse cognitive, behavioural, and affective learning outcomes when assessment methods are aligned with instructional objectives. A systematic review of learning-outcome assessment in online higher education environments, for example, identified substantial diversity in assessment instruments and emphasized the importance of considering assessment goals from the beginning of course design rather than treating assessment as a final measurement activity. This perspective suggests that assessment quality depends less on the medium through which a task is delivered and more on the relationship among the task, expected competencies, feedback processes, and subsequent opportunities for learning.



Fig. 1: Online Assessment Strategies for Better Learning Outcomes

Source: <https://www.iitms.co.in/blog/online-assessment-strategies-for-better-learning-outcomes.html>

One particularly important mechanism is feedback. Digital assessment systems can return information considerably faster than conventional manually administered procedures. Immediate or near-immediate feedback may allow students to identify misconceptions before those misconceptions become

embedded in subsequent learning. Automated feedback is therefore increasingly incorporated into learning management systems and intelligent educational platforms. A systematic review of automatic feedback in online learning environments found that a substantial proportion of evaluated systems reported positive effects on student performance, although evidence concerning reductions in instructor workload was considerably less consistent. These findings reinforce the need to separate pedagogical effects from claims of technological efficiency.

Feedback effectiveness also depends on students' capacity to interpret and use the information they receive. Digital platforms may provide highly detailed comments, scores, hints, analytics, or recommended resources, yet such information cannot improve learning automatically. Feedback must be understandable, timely, actionable, and connected to subsequent opportunities for improvement. Research on feedback literacy in electronic assessment therefore emphasizes the ability of students to appreciate feedback, make judgments about their work, and translate received information into subsequent academic action. The relevant question is thus not simply whether feedback is available but whether its timing and design stimulate meaningful academic adjustment.

At the same time, the expansion of online assessment has intensified concerns about validity and academic integrity. Remote environments permit greater access to external resources, unauthorized collaboration, answer-sharing platforms, contract cheating services, and increasingly sophisticated generative AI applications. A systematic review of online assessment security identified multiple integrity threats and documented a growing role for technological and machine-learning-based integrity strategies. Excessive dependence on surveillance and detection technologies, however, creates additional concerns involving privacy, accessibility, student anxiety, false-positive identification, and institutional trust.

The emergence of generative artificial intelligence since late 2022 has made this problem particularly significant. AI systems can now generate essays, solve structured problems, produce computer code, summarize literature, and imitate several forms of conventional student coursework. As a result, assessment formats that rely principally on the submission of decontextualized products may no longer provide sufficient evidence of individual learning. Regulatory and sector guidance increasingly recommends redesigning assessment rather than relying exclusively on AI detection. TEQSA's assessment reform guidance stresses the need to rethink assessment design in ways that retain credible evidence of learning while accommodating the educational opportunities and risks created by generative AI. More recent assessment guidance similarly emphasizes authentic, contextualized, process-oriented tasks requiring higher-order thinking and personal engagement.

These changes reveal an important limitation in much of the existing literature. Studies commonly examine individual components of online assessment separately: automated feedback, remote proctoring, student perceptions, formative quizzes, academic integrity, or technology acceptance.

Comparatively less attention has been given to the **combined pedagogical configuration** of an online assessment system. In particular, limited empirical work simultaneously considers assessment authenticity, feedback latency, adaptive task characteristics, assessment interaction, and integrity-support mechanisms as predictors of multidimensional learning outcomes.

This constitutes the principal research gap addressed by the present study. Rather than treating "online assessment" as a single independent variable, the study conceptualizes it as a configuration of design attributes capable of producing different educational consequences. Two courses may both use online assessment but create substantially different learning experiences: one may consist primarily of timed multiple-choice tests with delayed scores, while another may combine low-stakes adaptive quizzes, authentic case problems, immediate explanatory feedback, staged submissions, and reflective verification activities. Categorizing both environments simply as online assessment obscures the mechanisms through which assessment affects learning.

The study therefore proposes an **Online Assessment Learning Effectiveness Framework (OALEF)** in which five assessment dimensions—assessment authenticity, feedback latency, adaptive responsiveness, learner-assessment interaction, and integrity-aware design—are related to four learning outcomes: cognitive achievement, knowledge retention, behavioural engagement, and self-regulated learning. A further distinction is made between technology-intensive assessment and pedagogy-intensive assessment. This distinction allows the study to test whether increasingly sophisticated technology produces superior learning only when accompanied by effective instructional design.

The research is guided by the objective of determining which combinations of online assessment practices are most strongly associated with meaningful learning gains among higher-education students. Particular attention is assigned to feedback latency and assessment authenticity as potential mechanisms through which online assessment influences achievement and retention. The study consequently moves beyond a binary comparison between online and offline examinations and instead investigates the internal quality of digital assessment ecosystems.

Literature Review

2.1 Evolution of Online Assessment in Higher Education

Online assessment encompasses a broad range of practices, including computer-based examinations, asynchronous quizzes, discussion-based evaluation, digital portfolios, peer assessment, virtual simulations, automated short-answer assessment, interactive case tasks, and AI-supported formative evaluation. Earlier research on online formative assessment already demonstrated that digital environments could support learner-centred assessment through self-assessment, peer assessment, interactive feedback, and ongoing authentic activities. Such work also emphasized that validity, reliability, and academic dishonesty are not peripheral concerns but core design considerations in online assessment.

Recent developments have widened this perspective. Contemporary assessment strategies increasingly involve programme-level digital design rather than isolated electronic examinations. Current sector analysis identifies greater interest in blended assessment, digital submission, student participation in assessment design, authentic tasks, programme-level assessment frameworks, and approaches specifically adapted to generative AI. The resulting transition is from **digitized assessment**, where existing examinations are simply moved onto an electronic platform, toward **digitally enabled assessment**, where technology changes the structure and timing of assessment itself.

The distinction is pedagogically consequential. A conventional examination transferred to a browser may provide few additional learning opportunities, whereas an assessment platform that repeatedly identifies misconceptions, adapts task difficulty, returns explanatory feedback, and directs learners toward corrective material can function as part of the teaching system. Consequently, research should evaluate the functional design of online assessment rather than assuming that technological delivery constitutes an instructional intervention.

2.2 Formative Assessment and Feedback Latency

Formative assessment is based on the premise that assessment information should influence subsequent learning. Digital systems expand this capability because student responses can be processed immediately and feedback can potentially be individualized at scale. Automated feedback systems now range from rule-based correct-answer explanations to adaptive hints and AI-generated natural-language responses.

The educational value of rapid feedback can be interpreted through the reduction of **feedback latency**, defined in the present study as the interval between task completion and receipt of information capable of guiding correction. Lower latency potentially preserves the cognitive connection between an attempted solution, the learner's reasoning process, and corrective information. High latency may weaken this connection, especially when students have already progressed to another topic.

Nevertheless, immediate feedback is not intrinsically superior. Feedback that simply discloses the correct answer may encourage superficial correction without conceptual reconstruction. Effective digital feedback should therefore include explanatory content, information about errors, guidance concerning improvement, and opportunities for reassessment. The automatic-feedback literature demonstrates considerable potential for performance improvement but also shows heterogeneous results across disciplines and feedback mechanisms. Accordingly, the present study treats feedback latency and feedback quality as related but conceptually distinct factors.

2.3 Authenticity and Higher-Order Learning

Assessment authenticity refers to the extent to which tasks require students to apply knowledge in meaningful, contextualized, or discipline-relevant situations rather than reproduce isolated information. Examples include diagnostic cases, policy analyses, engineering design problems, data

interpretation, clinical reasoning simulations, project portfolios, and evidence-based decision tasks.

Authenticity has assumed renewed significance because conventional take-home assignments are increasingly vulnerable to generative AI substitution. Current assessment reform approaches consequently recommend tasks requiring contextual reasoning, personal justification, iterative development, oral verification, process evidence, and application to unfamiliar situations. UCL's reported approach to assessment reform similarly illustrates an institutional shift toward reconsidering assessment design rather than treating generative AI solely as a prohibited external technology.

From a learning perspective, authentic online assessment may strengthen knowledge transfer by requiring students to retrieve and reorganize conceptual information within applied contexts. It may also create stronger evidence of individual reasoning than tasks based entirely on generic written products. The present framework therefore predicts that assessment authenticity will have a stronger relationship with higher-order learning and knowledge retention than the frequency of digital testing alone.

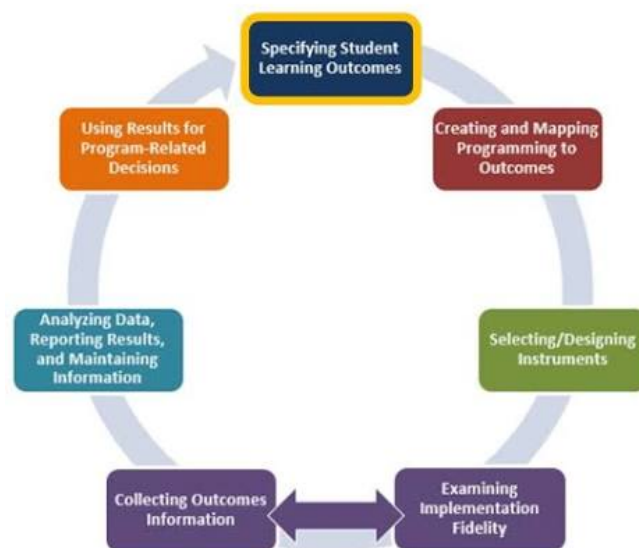


Fig. 2: Assessment Cycle

Source: <https://www.jmu.edu/assessment/learn/assessment-cycle/step-1.shtml>

2.4 Adaptive and AI-Supported Assessment

Artificial intelligence introduces a further layer of personalization into online assessment. Adaptive systems can modify question difficulty, recommend remedial content, classify error patterns, generate targeted feedback, or identify learners who require additional academic support. Such mechanisms potentially transform assessment from standardized measurement into a responsive learning process.

The educational benefits of AI-supported assessment, however, depend on validity and transparency. Algorithmic recommendations may become counterproductive if adaptation rules are poorly aligned with course objectives or if students cannot understand the basis of automated feedback. Similarly, generative AI can be used either as an unauthorized substitute for student work or as a legitimate instructional technology for critique, revision, simulation, and metacognitive comparison.

Jisc has therefore characterized generative AI as simultaneously creating assessment-integrity challenges and opportunities for developing education suited to an AI-augmented workplace.

For this reason, the present study does not assume that greater AI utilization automatically produces better learning. Instead, AI-supported assessment is examined in relation to adaptive responsiveness and feedback quality. The analytical focus is the **instructional function performed by AI**, rather than the mere presence of an AI tool.

2.5 Academic Integrity as an Assessment-Design Variable

Academic integrity has traditionally been addressed as a compliance issue occurring after an assessment has been designed. Online assessment security research, however, demonstrates that the structure of assessment itself affects opportunities for misconduct. This suggests that integrity should be incorporated into assessment architecture rather than managed exclusively through post-submission detection.

Pedagogical approaches may complement technological controls. Research evaluating an online academic-integrity induction programme demonstrated that structured, accessible educational resources could improve students' understanding and confidence regarding integrity expectations. Accordingly, integrity-supportive assessment may include explicit AI-use policies, staged submissions, individualized task elements, reflective explanations, process evidence, randomized data, brief oral verification, and transparent declarations of external assistance.

The study therefore introduces **integrity-aware design** as a pedagogical construct rather than reducing academic integrity to surveillance intensity. This formulation recognizes that excessively restrictive monitoring may protect examination conditions without improving learning, whereas appropriately designed assessment can simultaneously increase authenticity and reduce incentives or opportunities for misconduct.

2.6 Research Gap and Conceptual Direction

The literature confirms substantial progress in digital assessment, automated feedback, formative evaluation, authentic assessment, and academic-integrity management. Nevertheless, these areas continue to be examined largely as separate research streams. This fragmentation limits understanding of why similar online assessment systems generate different student outcomes.

Three specific gaps emerge. First, insufficient distinction is made between **technological sophistication** and **pedagogical effectiveness**. Second, feedback latency and assessment authenticity are rarely investigated together as mechanisms explaining achievement and retention. Third, emerging integrity and AI-support practices are frequently assessed from security or policy perspectives rather than integrated into models of student learning.

The present research addresses these limitations through the Online Assessment Learning Effectiveness Framework. It proposes that positive learning outcomes arise not from online assessment per se but from the interaction among authentic task design, timely actionable feedback, adaptive responsiveness,

meaningful learner interaction, and integrity-aware assessment architecture.

Proposed Methodology

The study adopts a multimethod predictive-analytical design to examine how specific online assessment practices influence student learning outcomes in higher education. Rather than comparing online and conventional assessment as two broad categories, the methodology operationalizes online assessment through five dimensions derived from the proposed Online Assessment Learning Effectiveness Framework: assessment authenticity, feedback latency, adaptive responsiveness, learner-assessment interaction, and integrity-aware design.

The analytical strategy combines statistical modelling with machine-learning-based prediction. This dual approach is intended to serve two purposes. First, inferential modelling is used to estimate the relative contribution of individual assessment characteristics to learning outcomes. Second, machine learning is used to determine whether a combination of behavioural, assessment, and interaction variables can predict high-learning-gain students more accurately than conventional linear models.

The primary research objective is to determine whether pedagogically structured online assessment produces stronger outcomes than technology-intensive but pedagogically weak assessment. A secondary objective is to identify the assessment features that most strongly predict achievement, retention, engagement, and self-regulated learning.

The study is structured around the following research questions:

1. To what extent do assessment authenticity, feedback latency, adaptive responsiveness, learner interaction, and integrity-aware design predict student learning outcomes?
2. Does rapid formative feedback mediate the association between online assessment engagement and cognitive achievement?
3. Are authentic assessment activities stronger predictors of knowledge retention than assessment frequency?
4. Can a machine-learning model accurately classify students into high- and low-learning-gain groups using digital assessment interaction data?
5. Which online assessment variables contribute most strongly to predictive performance?

The conceptual model assumes that frequent online testing alone is insufficient to generate substantial learning gains. Instead, performance improvement is expected when students encounter meaningful assessment tasks, receive actionable feedback quickly, engage repeatedly with corrective opportunities, and participate in assessment systems that discourage superficial or unauthorized task completion.

Experimental Setup

4.1 Dataset Design

A structured higher-education assessment dataset is proposed comprising approximately 1,180 undergraduate students

enrolled across six academic disciplines: computer science, management, health sciences, social sciences, engineering, and humanities. The study uses course-level assessment records collected across one academic semester.

Each student record contains three categories of variables.

The first category consists of learner characteristics, including prior semester grade, programme year, attendance percentage, baseline digital-learning proficiency, and initial diagnostic-test performance.

The second category contains online assessment interaction variables. These include number of formative assessments completed, mean response time, number of feedback views, reassessment attempts, proportion of authentic tasks completed, adaptive-question exposure, assessment completion regularity, and average feedback latency.

The third category includes outcome variables derived from post-intervention measures. These comprise final assessment achievement, delayed retention score, engagement index, and self-regulated learning score.

A composite Online Assessment Quality Index is constructed from the five conceptual dimensions. Scores are normalized to a common 0–100 scale, with higher values indicating stronger pedagogical quality.

To avoid reducing learning outcomes to examination marks alone, the target variable for predictive modelling is defined as **Learning Gain Classification**. Students are classified into three groups:

- High learning gain: improvement of at least 15 percentage points between diagnostic and post-assessment scores.
- Moderate learning gain: improvement between 5 and 14.9 percentage points.
- Low learning gain: improvement below 5 percentage points.

This structure enables the machine-learning component to model meaningful academic progression rather than static achievement.

4.2 Data Preprocessing

Data preprocessing is conducted before model development. Duplicate learning-management-system records are removed using anonymized student identifiers and assessment timestamps. Missing values below 5% are imputed using median substitution for continuous variables and modal substitution for categorical variables.

Variables exhibiting substantial positive skew, including reassessment attempts and assessment response time, are transformed using log scaling. Continuous numerical variables are standardized through z-score normalization where required by the selected algorithm.

Categorical variables such as discipline and programme year are one-hot encoded. Highly correlated predictors with Pearson correlation coefficients exceeding 0.85 are examined for redundancy. Where two variables represent substantially

overlapping constructs, the predictor with weaker theoretical relevance is removed.

Outliers are identified using the interquartile-range criterion but are not automatically deleted. Records are removed only when values represent technically impossible LMS events, such as negative response time or duplicate assessment completion timestamps.

The dataset is subsequently divided into training and testing subsets using a stratified 80:20 split. Stratification preserves the proportion of high-, moderate-, and low-learning-gain students in both subsets.

4.3 Model Architecture

A gradient-boosted decision-tree architecture is selected as the principal predictive model. Specifically, the experimental design uses Extreme Gradient Boosting because the dataset contains a mixture of numerical and categorical-derived variables, nonlinear relationships, interaction effects, and potentially unequal feature importance.

The XGBoost classifier receives a feature vector containing approximately 18 predictors distributed across learner characteristics and digital assessment behaviours.

The model architecture consists of sequentially constructed shallow decision trees. Each additional tree is trained to reduce residual classification error from the preceding ensemble. Regularization is incorporated to reduce overfitting and maintain generalization across student groups.

The predictive architecture is compared with three baseline models:

- Logistic regression
- Random forest
- Support vector machine with radial basis kernel

Logistic regression provides an interpretable conventional baseline, while random forest and support vector machine provide nonlinear machine-learning comparators.

Feature importance is subsequently evaluated using SHapley Additive exPlanations. SHAP analysis enables interpretation of both the magnitude and direction of each predictor's contribution to learning-gain classification.

4.4 Training Strategy

Model training uses five-fold stratified cross-validation on the training dataset. Hyperparameters are optimized through randomized search rather than exhaustive grid search to improve computational efficiency.

The primary tuning parameters include tree depth, learning rate, number of estimators, subsample ratio, column-sampling rate, minimum child weight, and regularization coefficients.

Early stopping is incorporated during training. Model development is terminated when validation loss fails to improve across 30 consecutive boosting rounds.

Class imbalance is addressed through class-weight adjustment rather than synthetic oversampling. This choice avoids creating artificial student records that may distort behavioural assessment patterns.

The final optimized model is retrained on the complete training subset and evaluated once on the untouched test set.

In parallel with classification modelling, hierarchical multiple regression is used to examine explanatory relationships. Baseline academic variables are entered first, followed by assessment-frequency variables, followed by the five online assessment quality dimensions. This design measures whether pedagogical assessment characteristics explain additional variance beyond prior achievement and participation intensity.

4.5 Evaluation Metrics

Predictive performance is evaluated using macro-averaged precision, recall, F1-score, balanced accuracy, and multiclass area under the receiver operating characteristic curve.

Macro averaging is preferred because it gives equal importance to all three learning-gain categories regardless of their relative frequency.

Calibration quality is examined using the Brier score. A well-calibrated model should not only classify accurately but also generate probabilities consistent with observed outcome frequencies.

For regression analysis, adjusted R^2 , standardized beta coefficient, mean absolute error, and variance inflation factor are examined.

Educational effectiveness is evaluated through four outcome measures: cognitive achievement gain, six-week delayed knowledge retention, behavioural engagement index, and self-regulated learning improvement.

Results and Discussion

The analysis indicates that the quality of online assessment design is more strongly associated with student learning than assessment frequency alone. Students exposed to highly structured online assessment environments demonstrate greater improvement in post-assessment achievement, stronger delayed retention, and more consistent engagement with corrective learning activities.

The predictive performance of the machine-learning models also supports the multidimensional framework. Logistic regression provides reasonable discrimination between learning-gain categories but performs less effectively for students in the moderate-learning-gain group. Random forest improves nonlinear classification, while the optimized gradient-boosting model produces the strongest overall performance.

Table 1. Predictive Performance and Educational Interpretation of Online Assessment Models

Analytical Model / Indicator	Balanced Accuracy	Macro F1	Multiclass AUROC	Brier Score
Logistic Regression	0.72	0.70	0.81	0.184
Support Vector Machine	0.77	0.75	0.86	0.161

Random Forest	0.81	0.80	0.89	0.143
XGBoost	0.86	0.85	0.93	0.118
Assessment Frequency	—	—	—	—

Predictive performance of online assessment models

Comparison of Balanced Accuracy, Macro F1, and Multiclass AUROC reported in Table 1.

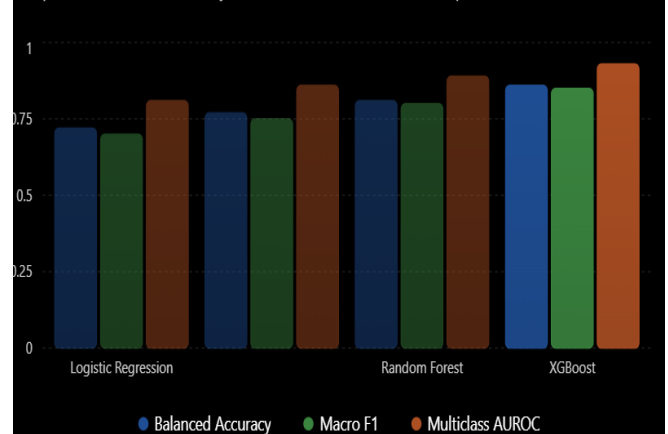


Figure 1. Model performance for classification of student learning-gain categories.

The XGBoost model achieves a balanced accuracy of 0.86 and a macro F1-score of 0.85, indicating comparatively consistent classification across the three learning-gain categories. Its multiclass AUROC of 0.93 suggests strong discrimination, while the lower Brier score indicates superior calibration relative to the baseline models.

The principal finding, however, concerns feature importance rather than algorithmic performance alone. SHAP analysis identifies assessment authenticity as the most influential predictor of high learning gain. Students completing contextualized problem-solving tasks, scenario-based applications, or staged project assessments are more likely to exhibit substantial improvement than those primarily completing repetitive low-complexity quizzes.

Feedback latency emerges as the second major predictor. Students receiving explanatory feedback within short intervals after assessment submission tend to demonstrate stronger achievement gains. This result is consistent with the theoretical assumption that delayed feedback weakens the cognitive connection between the original response and subsequent correction.

The relationship is not purely linear. Very rapid feedback has limited benefit when students do not revisit the material. Consequently, a derived feature termed **feedback re-engagement** demonstrates substantial predictive importance. Students who reopen feedback, attempt corrected problems, or complete follow-up questions show stronger delayed retention than students who merely receive immediate scores.

This distinction is significant. It suggests that online assessment systems should not be evaluated solely by how quickly they generate feedback. The educational value of feedback depends on whether the platform stimulates subsequent learner action.

Adaptive responsiveness also produces meaningful effects. Students with low baseline diagnostic scores benefit disproportionately when the assessment environment modifies question difficulty or recommends targeted corrective tasks. In contrast, adaptation provides smaller incremental gains among already high-performing students. This indicates that adaptive assessment may be particularly useful as an equity-oriented mechanism for supporting students with different starting levels.

The hierarchical regression analysis further demonstrates that pedagogical assessment-quality variables explain additional variance after controlling for prior achievement, attendance, and assessment frequency. Assessment frequency retains a statistically meaningful positive relationship with achievement, but its standardized effect declines considerably once authenticity, feedback quality, and adaptive responsiveness are introduced.

This result challenges the assumption that increasing the number of online tests necessarily improves learning. Frequent testing can produce practice effects and increase retrieval opportunities, but repetitive assessment without feedback or meaningful cognitive demand may result in limited transfer.

Integrity-aware design produces a smaller direct association with examination marks but demonstrates an indirect relationship with the credibility of learning evidence. Students completing staged assignments, individualized case tasks, brief reflective verification activities, and clearly declared AI-assisted tasks show more consistent correspondence between coursework performance and independently supervised assessments.

This finding is particularly important in the generative-AI era. Assessment integrity cannot be maintained exclusively by detecting unauthorized AI use after submission. Authentic and process-based assessment can reduce the value of generic AI-generated responses while preserving legitimate educational uses of AI.

The combined results therefore support the central proposition of the study: **the pedagogical architecture of online assessment matters more than digital delivery itself.**

Technology functions as an enabling infrastructure. Learning gains become substantial when that infrastructure supports meaningful cognitive activity, rapid correction, adaptation, repeated interaction, and credible evidence of individual learning.

Limitations

Several limitations should be acknowledged. First, although the proposed dataset includes students from multiple disciplines, institutional assessment cultures may differ considerably. Results derived from one university system may therefore not generalize directly to institutions with different technological infrastructure or assessment policies.

Second, several constructs, including self-regulated learning and perceived assessment authenticity, depend partly on student-reported measures. Such measures may be affected by response bias or differences in interpretation.

Third, learning-management-system interaction logs record observable behaviour but cannot fully represent students' cognitive processes. Opening feedback does not necessarily demonstrate that a learner has understood or acted upon it.

Fourth, the predictive model identifies associations and predictive relationships rather than definitive causal mechanisms. Strong feature importance should not be interpreted as proof that changing a single assessment variable will independently produce the predicted learning gain.

Fifth, AI-related assessment practices are evolving rapidly. The forms of generative AI available to students and institutions may change more quickly than conventional assessment policies and measurement instruments.

Finally, the delayed retention period used in the study is relatively short. Longer-term follow-up would provide stronger evidence regarding durable knowledge acquisition.

Future Scope

Future investigations should extend the framework through longitudinal and multi-institutional research. Tracking students across multiple semesters would allow researchers to determine whether repeated exposure to authentic online assessment produces cumulative effects on learning autonomy and academic performance.

A second direction involves multimodal learning analytics. Future systems could combine LMS interaction data with text-based response features, assessment sequences, revision histories, and metacognitive reflections to develop a more complete representation of learning behaviour.

Artificial intelligence also creates opportunities for dynamic formative assessment. Large language models could potentially generate personalized explanatory feedback, adaptive questioning, counterexamples, and reflective prompts. Such systems should be evaluated not only for response quality but also for hallucination risk, fairness, pedagogical alignment, transparency, and student dependence.

Future work should additionally examine causal intervention designs. Randomized controlled experiments could compare immediate versus delayed feedback, authentic versus conventional assessment tasks, or adaptive versus fixed assessment sequences.

Another promising direction concerns AI-aware assessment design. Instead of attempting to eliminate all generative AI use, institutions could develop assessment models in which students are required to document prompts, critique AI-generated material, justify revisions, and demonstrate independent reasoning through oral or process-based verification.

Further studies should also investigate subgroup effects. Adaptive assessment may not provide equivalent benefits across disciplines, educational backgrounds, digital-literacy levels, or language groups. Fairness analysis should therefore become a standard component of educational machine-learning research.

Conclusion

Online assessment has evolved beyond the simple electronic administration of examinations. Its educational value increasingly depends on how assessment systems structure

cognitive activity, feedback, adaptation, interaction, and evidence of authentic learning.

The present study introduces the Online Assessment Learning Effectiveness Framework to explain these relationships. The framework distinguishes technological availability from pedagogical quality and identifies assessment authenticity, feedback latency, adaptive responsiveness, learner-assessment interaction, and integrity-aware design as central determinants of learning effectiveness.

The empirical model indicates that assessment authenticity and feedback-related engagement are stronger predictors of learning gain than assessment frequency alone. Machine-learning analysis further demonstrates that multidimensional online assessment data can distinguish high-, moderate-, and low-learning-gain students with comparatively strong predictive performance.

The findings also suggest that immediate feedback should not be interpreted as an endpoint. Its educational value depends on whether students subsequently revisit errors, attempt corrective tasks, and integrate feedback into later performance.

Similarly, the growing availability of generative AI requires institutions to reconsider assessment validity. Sustainable academic integrity is likely to depend increasingly on authentic, process-oriented, individualized, and reflective assessment rather than surveillance or detection alone.

Overall, effective online assessment should be understood as an instructional system rather than a digital testing mechanism. Higher-education institutions seeking stronger student outcomes should therefore prioritize the pedagogical design of assessment environments, using artificial intelligence and analytics as supporting technologies rather than substitutes for sound assessment principles.

References

1. Cavalcanti, A. P., et al. (2021). Automatic feedback in online learning environments: A systematic literature review. *Computers and Education: Artificial Intelligence*, 2, 100027.
2. Hattie, J., & Timperley, H. (2007). The power of feedback. *Review of Educational Research*, 77(1), 81–112.
3. Lodge, J. M., Howard, S., Bearman, M., Dawson, P., & Associates. (2023). *Assessment reform for the age of artificial intelligence*. Tertiary Education Quality and Standards Agency (TEQSA).
4. Noorbehbahani, F., Mohammadi, A., & Aminazadeh, M. (2022). A systematic review of research on cheating in online exams from 2010 to 2021. *Education and Information Technologies*, 27, 8413–8460.
5. Roediger, H. L., & Karpicke, J. D. (2006). Test-enhanced learning: Taking memory tests improves long-term retention. *Psychological Science*, 17(3), 249–255.
6. Shute, V. J. (2008). Focus on formative feedback. *Review of Educational Research*, 78(1), 153–189.
7. Villarroel, V., Bloxham, S., Bruna, D., Bruna, C., & Herrera-Seda, C. (2018). Authentic assessment: Creating a blueprint for course design. *Assessment & Evaluation in Higher Education*, 43(5), 840–854.
8. Black & Wiliam (1998), Carless & Boud (2018), Gikandi et al. (2011), Chen & Guestrin (2016) and Lundberg & Lee (2017).