Designing an AI-Resilient Assessment Framework in Open and Distance Learning

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ABSTRACT

The emergence of generative artificial intelligence tools such as ChatGPT, Copilot, and Gemini has disrupted long-established ideas about teaching, learning, and assessment in higher education, especially within the Open and Distance Learning (ODL) context. Evidence from recent literature shows that traditional assessment formats, particularly take-home assignments and written tasks, are increasingly vulnerable to AI automation, which subsequently raises significant concerns about academic integrity. This conceptual paper proposes the AI-Resilient Assessment Framework (ARAF), a theoretically grounded framework that positions AI not as a threat but as a catalyst for higher-order learning. By synthesising evidence from GenAI assessment reviews, AI policy studies, authentic assessment strategy, and research on AI literacy, ARAF introduces three core principles, namely Transparency, Reflection, and Authenticity, supported by a set of Institutional Enablers. The framework shifts assessment design away from policing AI use and toward fostering ethical engagement, metacognitive reasoning, contextual judgement, and real-world performance. It offers both practical and theoretical guidance for ODL institutions that aim to implement sustainable, ethical, and future-ready assessment strategies within an AI-enhanced learning environment.

Keywords
Generative artificial intelligence; Assessment design; Transparency; Reflection; Authenticity; AI-resilient; Open and distance learning (ODL)

Introduction

The evolution of generative AI has fundamentally disrupted assessment practices in higher education. GenAI systems can produce essays, solve problems, draft explanations, and refine language instantly, and these capabilities intensify concerns about authorship, academic integrity, and the validity of student work (Kofinas et al., 2025; Evangelista, 2025). These concerns are particularly amplified in ODL contexts, where assessments frequently rely on independent and unsupervised tasks (Omar et al., 2025).

Recent research consistently notes that detection-based approaches are unreliable and pedagogically misaligned with emerging expectations for Education 5.0 (Bittle & El-Gayar, 2025; Ifelebuegu, 2023). Empirical studies have shown that AI detection tools frequently produce high rates of false positives thereby penalising legitimate student writing, particularly among non-native English speakers, and raising concerns about fairness and validity (Giray, 2025; Kofinas et al., 2025). Rather than supporting learning, detection practices often encourage surveillance-oriented assessment cultures, foster mistrust between educators and students, and promote adversarial behaviours such as prompt obfuscation or strategic rewriting (Deep et al., 2025; Kofinas et al., 2025). In addition, detection accuracy varies across disciplines, text genres, and AI models, hence making consistent enforcement difficult and undermining confidence in assessment decisions (Giray et al., 2025). As AI systems evolve rapidly, detection tools also struggle to remain up to date, further limiting their reliability as a long-term solution. Hence, scholars argue for non-resistant or AI-resilient assessment approaches that acknowledge AI as part of modern thinking and problem-solving (Roe et al., 2025).

Global analyses of GenAI in assessment (Xia et al., 2024; Giannakos et al., 2024) highlight three persistent challenges:

1. Authenticity erosion: tasks that can be fully or partially automated lose discriminatory power.
2. Transparency gaps: unclear expectations produce inconsistent and unethical AI use.

3. Limited reflective integration: students rarely justify or critique AI-generated content.

These challenges demand a new assessment paradigm where academic integrity is upheld not by surveillance but by critical engagement, contextual judgement, and ethical accountability. Thus, this paper proposes the AI-Resilient Assessment Framework (ARAF), by synthesising insights from GenAI research, authentic assessment strategy, and AI literacy to guide ODL institutions in reshaping assessment for an AI-infused era.

Literature Review

GenAI and Vulnerabilities in Traditional Assessment

Empirical studies show that GenAI severely compromises traditional written and language-dependent assessments. Kofinas et al. (2025) found that authentic assessments, which were long assumed to be more resistant to plagiarism, are increasingly vulnerable because AI can generate responses that appear contextually specific. Scoping reviews by Xia et al. (2024) and Giannakos et al. (2024) also further demonstrate that GenAI has changed assessment from a product-based output to a co-generated performance, making it necessary to distinguish the learner's contribution from machine assistance.

Detection-Driven Approaches

Detection tools are increasingly ineffective and ethically problematic. Evangelista (2025) argues that AI detection cannot provide reliable evidence of misconduct, and relying on such tools threatens fairness and due process. Kofinas et al. (2025) also show that detection systems undermine trust, disproportionately target non-native speakers, and produce inconsistent results across platforms. Moreover, Roe et al. (2025) caution that detection-centric policies encourage hidden AI use, rather than teaching students how to use AI ethically and transparently.

Authentic Assessment in an AI Ecosystem

Authentic assessment remains essential in an AI-enhanced educational ecosystem, but it requires deliberate redesign. Recent studies converge on three interrelated needs that underpin effective and credible assessment practices in the presence of generative, as the following:

- Contextual complexity that AI cannot easily replicate (Ifelubuegu, 2023).
- Real-world decision-making rather than content reproduction (Gonsalves, 2025).
- Integration of AI critique and justification (Hutson, 2025).

First, assessments must incorporate contextual complexity that AI cannot easily replicate. Ifelebuegu (2023) argues that tasks grounded in rich, situational, and discipline-specific contexts are less susceptible to automation because they require learners to interpret nuanced conditions, constraints, and human considerations. Pedagogically, such complexity shifts assessment away from generic task completion towards situated reasoning, where students must demonstrate understanding of context, intent, and consequence. In AI-enhanced environments, contextual complexity also functions as a safeguard for authenticity by foregrounding learners' interpretive judgement rather than their ability to generate polished outputs.

Second, authentic assessment should prioritise real-world decision-making rather than content reproduction. Gonsalves (2025) emphasises that GenAI performs well in reproducing conventional academic genres but struggles with tasks that require situated judgement, trade-off analysis, and ethical or professional reasoning. From a pedagogical standpoint, decision-focused assessments align with higher-order learning outcomes by requiring students to justify choices, evaluate alternatives, and respond to uncertainty, all of which are central to professional practice. When embedded in assessment design, this emphasis ensures that AI functions as a contextual aid rather than a substitute for human reasoning.

Third, authentic assessment in an AI ecosystem must explicitly support the integration of AI critique and justification. Hutson (2025) highlights the importance of requiring students to articulate how AI tools were used, what was accepted or rejected, and why particular outputs were refined or challenged. This requirement transforms AI use into an object of critical reflection rather than an invisible shortcut. Pedagogically, such practices support metacognition, ethical awareness, and AI literacy by making students' reasoning processes visible and assessable. They also reinforce transparency and accountability, which are essential for maintaining trust in AI-enhanced assessment practices.

Consistent with this perspective, assessment reform work by Le (2024) underscores the importance of ethical, context-driven approaches that integrate AI as a support tool while safeguarding academic credibility. Together, these insights suggest that authentic assessment in AI-enhanced environments must be intentionally designed to foreground human agency, disciplinary judgement, and reflective engagement, rather than relying on surface indicators of originality or technical proficiency alone.

AI Literacy, Reflection, and Ethical Readiness

AI literacy is emerging as a foundational competence in higher education and ODL. Ng and Leung (2024) show that students require dual literacy, i.e. the ability to use AI and the ability to reflect critically on its limitations. Similarly, Hutson (2025) argues for a revised taxonomy incorporating AI-mediated reasoning, prompting educators to embed structured reflection (e.g. prompt logs, justification notes, critique tasks). Meanwhile, Education 5.0 literature (e.g. Giannakos et al., 2024) connects AI literacy with ethical readiness, which in turn highlighting the necessity of reflective practice for sustaining lifelong learning.

Institutional Policies and Governance

Stracke et al. (2025) reveal significant inconsistencies across higher-education AI policies and call for:

- transparent guidelines
- ethical governance frameworks
- capacity-building for educators
- fairness and student protections

Rassia and Manousou (2025) further argue that ODL institutions must update assessment regulations to reflect AI-enabled realities.

Methods

Research Design

This study adopts a conceptual research design, an approach commonly used in emerging fields of educational technology where theoretical reframing is necessary to address rapidly evolving pedagogical challenges. Given the transformative impact of generative artificial intelligence on assessment practices, conceptual analysis provides an appropriate methodological foundation for synthesising insights from diverse bodies of literature and for constructing the AI-Resilient Assessment Framework (ARAF).

Relevant studies were identified through structured searches of major academic databases, including Scopus, Web of Science, and Google Scholar. Search terms combined key concepts related to generative AI and assessment, such as *generative artificial intelligence*, *AI in assessment*, *academic integrity*, *authentic assessment*, *AI-resilient assessment*, and *higher education*. The review focused primarily on journal articles published between 2023 and 2025, as it reflects the rapid emergence of generative AI technologies in educational contexts.

Data Analysis

The development of the ARAF framework emerged through an iterative synthesis of evidence across several domains of research. Scoping reviews of generative AI in higher education (Xia et al., 2024; Giannakos et al., 2024) provided insights into how GenAI is reshaping the nature of academic work and exposing new forms of assessment vulnerability. Studies on AI integrity and policy (Kofinas et al., 2025; Evangelista, 2025; Stracke et al., 2025) contributed an understanding of institutional responsibilities and the need for regulatory clarity in AI-enhanced learning environments. Research on authentic assessment (Ifelubuegu, 2023; Gonsalves, 2025) offered a foundation for analysing how human judgement, contextualised reasoning, and real-world performance can serve as buffers against AI over-reliance.

Additionally, frameworks on AI literacy and reflective practice (Ng & Leung, 2024; Hutson, 2025) informed the need for metacognitive engagement in AI-supported assessment. Studies focusing on ODL adoption and assessment practices (Omar et al., 2025) further highlighted the challenges and opportunities faced by learners who engage with AI in independent, decentralised learning environments.

Through the triangulation of these diverse sources, three recurring pedagogical imperatives emerged as central to designing AI-resilient assessments: Transparency, Reflection, and Authenticity. These principles consistently appeared as critical safeguards in GenAI-enabled learning environments, and their effectiveness was shown to depend heavily on the presence of Institutional Enablers such as AI policies, educator training, and learner support structures. The convergence of these conceptual threads ultimately shaped the formulation of the ARAF model presented in this paper.

Results and Discussion

AI-Resilient Assessment Framework

The AI-Resilient Assessment Framework (ARAF) reconceptualises assessment as a reflective, ethical, and collaborative partnership between human intelligence and generative AI. It shifts assessment practices away from approaches rooted in surveillance and prohibition, which are increasingly ineffective in digital learning environments, and moves instead toward models that promote learner agency, critical judgement, and transparent engagement with AI. These competencies are especially essential within ODL, where learners frequently work autonomously, rely heavily on technological tools, and navigate their learning outside traditional classroom structures. Across the reviewed literature, three principles, i.e. Transparency, Reflection, and Authenticity, consistently emerge as central to designing assessments that remain credible, meaningful, and equitable in AI-rich ODL ecosystems. These principles operate within, and are reinforced by, a set of institutional enablers that ensure assessment practices remain consistent and fair across geographically dispersed learner populations.

Table 1. Conceptual mapping of reviewed studies to the AI-Resilient Assessment Framework (ARAF)

Author(s) & Year	Findings from the Study	Transparency	Reflection	Authenticity	Institutional Enablers
Kofinas, Tsay & Pike (2025)	Detection tools are unreliable; academic integrity requires systemic reform	Transparency as a trust-building mechanism	Metacognitive engagement reduces misconduct	Authentic assessment must evolve	Institutions must replace detection with ethical policy structures
Xia et al. (2024)	Identifies risks of automation, lack of policy clarity, and need for new frameworks	Transparency gaps identified as the biggest institutional weakness	Supports metacognitive strategies to reduce blind AI reliance	Calls for redesign of authentic assessments	Recommends sector-wide governance structures
Evangelista (2025)	Detection is ineffective; ethical clarity is key	Strong emphasis on explicit rules, permissions, and disclosure	Encourages justification of AI-assisted reasoning	Advocates higher-order tasks requiring human interpretation	Requires AI ethics policies and faculty training

Author(s) & Year	Findings from the Study	Transparency	Reflection	Authenticity	Institutional Enablers
Stracke et al. (2025)	Provides a policy framework for governance, ethics, transparency	Directly emphasises transparent and fair AI use rules	Supports reflective, critical digital practice	Suggests real-world ethically grounded assessments	Strong institutional guidance: governance, training, accountability
Giannakos et al. (2024)	AI changes cognitive processes; demands metacognitive skills and ethical judgement	Supports open AI-use declarations	Emphasises reflection and critical evaluation of AI limitations	Argues assessments should be contextual and problem-centred	Highlights Education 5.0, digital ethics, AI readiness
Omar et al. (2025)	ODL institutions increasingly embed AI to support learners in real tasks	Advocates clear communication on how AI may be used	Encourages critical interrogation of AI outputs	Reinforces authentic online assessments requiring human agency	Notes importance of institutional guidance for ODL
Ifelubuegu (2023)	AI undermines surface-level tasks; deep tasks still learner-dependent	Requires students to indicate where AI is used	Encourages metacognitive explanations to separate student reasoning from AI output	Shows need for complex, real-world tasks	Recommends institutional policies reinforcing authentic assessment
Hutson (2025)	Introduces AI-infused reflection framework	Argues for transparent prompt-sharing	Strongly supports reflective logs, self-evaluation, critique	Reflection integrated to authentic digital artefact creation	Suggests educator upskilling in AI literacy
Ng & Leung (2024)	Reflection and AI literacy is ethical, critical engagement	Students must disclose and explain AI use	Reflection is the foundation of valid learning with AI	Suggests authentic reasoning tasks	Calls for institutional frameworks for AI-literacy development
Roe, Perkins & Giray (2025)	Non-resistant assessment fosters metacognition	Transparency helps evaluate learners' AI engagement	Reflection demonstrates human cognition beyond AI	Authentic tasks better reveal reasoning	Recommends institutional training for educators
Rassia & Manousou (2025)	ODL needs updated regulations for AI usage	Clear transparent rules required	Reflection as part of regulatory compliance	Authentic ODL assessment essential	Recommends systemic regulatory updates
Le (2024)	Ethical, context-based redesign required in GenAI era	Calls for transparent assessment expectations	Encourages reflective ethical judgement	Emphasises real-world complexity in tasks	Highlights institutional responsibility for ethical assessment reform

Transparency in AI-Enabled ODL Environments

Transparency serves as the foundation for responsible AI integration and is particularly crucial in ODL contexts where educators cannot observe learner behaviour directly. The literature consistently stresses that without explicit

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expectations, ODL learners may struggle to distinguish appropriate from inappropriate AI use. Stracke et al. (2025) argue that transparent institutional policies are essential in distance education to ensure a shared understanding of ethical expectations across diverse learner populations. Within ODL, transparency also addresses a heightened risk of ambiguity. Unlike face-to-face environments, where clarification can occur informally and immediately, ODL learners depend primarily on written task instructions, LMS guidance, and asynchronous feedback to interpret assessment expectations.

From an assessment design perspective, transparency must therefore be operationalised through explicit and visible assessment artefacts, rather than relying on abstract policy statements alone. At the task level, this involves embedding clear AI-use expectations directly into assessment briefs, specifying not only whether AI tools may be used, but also *how*, *for what purposes*, and *at which stages* of the task. For example, instructions may distinguish between permitted uses such as idea generation or language refinement and prohibited uses such as full answer generation, thereby reducing interpretive uncertainty for learners working independently.

Transparency also translates into rubric design, where assessment criteria explicitly reference reasoning, justification, and process rather than focusing solely on final outputs. By including criteria related to explanation of decisions, evaluation of AI-generated content, or reflective commentary on AI use, rubrics signal that learning is judged on cognitive engagement and judgement, not on surface-level polish. Such alignment between task instructions and rubrics is particularly important in ODL, where assessment criteria often function as the primary interpretive guide for learners.

Roe et al. (2025) further propose AI-use declarations and annotated drafts as mechanisms that make learners' cognitive contributions visible and assessable. In practice, AI-use disclosure forms or short appendices can require students to state which tools were used, at what stage, and how outputs were adapted or rejected. Annotated drafts and revision logs extend this transparency by documenting the evolution of ideas over time, allowing tutors to assess learning processes despite the absence of physical classroom interaction. Evangelista (2025) similarly emphasises that such practices support ethical reasoning and self-regulation, which are essential competencies for self-directed ODL learners.

Additional transparency mechanisms discussed in the literature include learner contracts or integrity statements that explicitly outline mutual responsibilities regarding AI use, as well as tutor-provided model examples demonstrating acceptable and unacceptable AI-supported work. These examples are particularly valuable in ODL settings, as they compensate for the lack of informal clarification and reduce reliance on trial-and-error interpretation.
For ODL institutions, transparency therefore functions not merely as a safeguard against misconduct, but as an instructional design strategy that structures learner behaviour, supports ethical judgement, and builds trust. When embedded coherently across task instructions, rubrics, disclosure mechanisms, and exemplars, transparency enables AI-enhanced assessment practices that are both credible and pedagogically meaningful in distance learning environments.

Reflection as a Metacognitive Anchor for ODL Learners

Reflection emerges from the literature as the central cognitive safeguard against uncritical reliance on AI. This is particularly significant in ODL, where learning processes occur privately and learners frequently use digital tools including AI for support, feedback, and idea generation. Because educators in ODL cannot observe the learning process directly, reflective evidence becomes essential in demonstrating human reasoning within AI-assisted work.

Roe et al. (2025) highlight metacognition as a critical skill for navigating AI-rich environments. Ng and Leung (2024) further argue that reflective engagement helps learners evaluate AI accuracy, an especially important skill in ODL contexts, where students may rely more heavily on AI for explanations, summarisation, or problem-solving due to reduced immediate tutor contact. Reflective mechanisms suited to ODL include:

- prompt logs documenting interactions with AI
- justification paragraphs explaining final choices
- reflective commentaries embedded within digital submissions

- iterative learning journals uploaded to LMS platforms

Hutson (2025) stresses that integrating AI-specific reflection tasks can advance both AI literacy and disciplinary learning. For ODL students who often engage with coursework asynchronously and independently, reflection becomes not just a pedagogical strategy, but a means of making learning processes visible, verifiable, and assessable.

Authenticity as a Response to AI-Vulnerable Assessment in ODL

Authenticity is repeatedly highlighted across the literature as the most effective antidote to AI-enabled shortcuts. In ODL environments, where traditional examinations and take-home assignments are particularly vulnerable to AI substitution, authenticity becomes indispensable for safeguarding the validity of student learning evidence.

Ifelebuegu (2023) emphasises that authentic tasks require human judgement, contextual reasoning, and the integration of lived experiences which AI cannot easily replicate. The relevance of authenticity is amplified in ODL contexts because:

- learners often complete assessments remotely without proctoring
- AI tools are readily accessible during self-directed study
- traditional assessments (e.g. essays) are more susceptible to AI misuse

Authentic assessment formats recommended for ODL include:

- scenario-based analyses requiring contextual adaptation
- community or workplace-embedded problem solving
- digital artefact production with iterative human design choices
- reflective portfolios combining AI-assisted and learner-generated components

Le (2024) highlights that authentic tasks also promote ethical awareness when they require learners to justify their integration of AI into real-world problem-solving. Thus, authenticity does not merely make tasks more resilient to AI, but it makes assessment more meaningful within the flexible, technology-rich structure of ODL.

Institutional Enablers as a Critical Requirement for ODL Sustainability

The literature strongly indicates that the viability of AI-resilient assessment in ODL depends on institutional coherence. Unlike campus-based systems, ODL institutions must ensure uniform experiences across large, geographically dispersed learner groups who may not have direct contact with lecturers. Institutional enablers therefore ensure consistency, fairness, and transparency in AI policy implementation. Stracke et al. (2025) identify key governance mechanisms, including:

- ethical AI-use guidelines
- systematic professional development for educators
- AI literacy programmes for students
- clear and transparent assessment regulations

For ODL environments, these enablers are not optional but are structural necessities. Omar et al. (2025) and Rassia and Manousou (2025) show that institutional consistency is critical to reducing confusion among distance learners and enabling tutors to evaluate AI-assisted work fairly. In the absence of such enablers, AI-resilient assessment risks becoming fragmented, inconsistently applied, or dependent on individual tutor interpretation. These conditions can undermine assessment credibility and learner trust in ODL systems. Thus, institutional readiness becomes the backbone of the ARAF model, ensuring that transparency, reflection, and authenticity are systematically embedded rather than sporadically practised across ODL programmes.

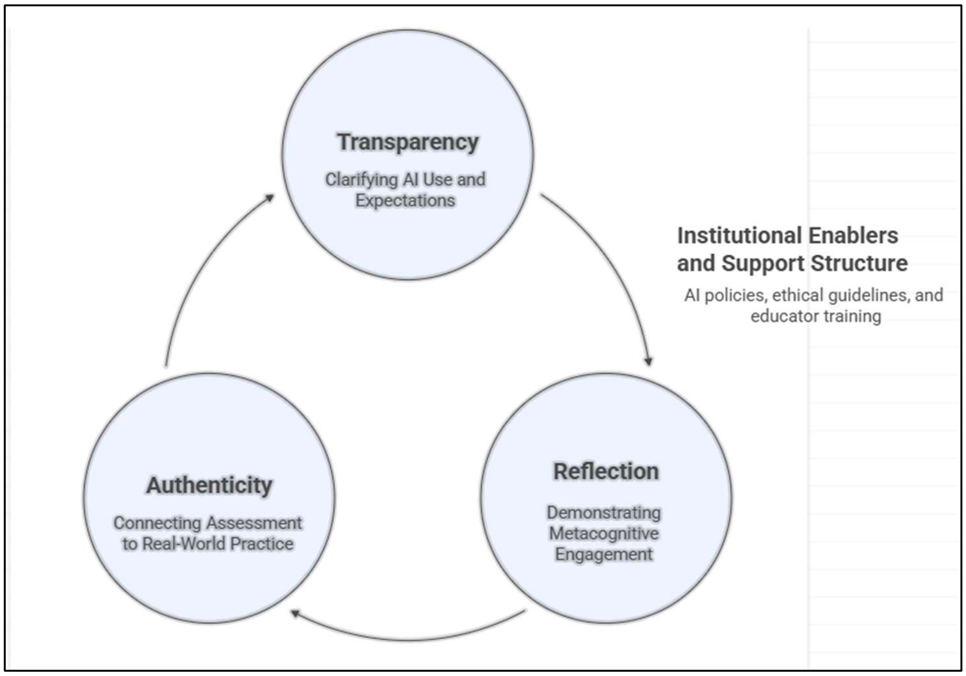

Figure 1. Conceptual model of the AI-Resilient Assessment Framework (ARAF)

Figure 1 illustrates the structural relationship among the three core principles of the ARAF model, i.e. Transparency, Reflection, and Authenticity, alongside the institutional enablers that support their implementation within Open and Distance Learning (ODL) environments. The diagram positions these principles in a circular, interconnected sequence to emphasise their dynamic and mutually reinforcing nature. Transparency serves as the starting point, underscoring the need for clear communication of expectations and ethical guidelines regarding AI use. This clarity enables learners to engage in meaningful Reflection, where they critically evaluate their interactions with AI and articulate the reasoning behind their decisions. Reflection then naturally supports Authenticity, prompting learners to apply knowledge in contextually rich, real-world situations where human judgement is essential. Surrounding these principles are the institutional enablers, such as AI policies, ethical guidelines, and educator training that provide the structural support necessary for consistent and sustainable adoption across dispersed ODL learner populations. Together, these components form a cohesive system that promotes ethical, transparent, and contextually grounded assessment in AI-enhanced learning environments.

Conclusion

This conceptual paper proposes the AI-Resilient Assessment Framework (ARAF) as a structured model for reimagining assessment in Open and Distance Learning (ODL) settings. Grounded in the integration of constructivist principles, authentic assessment theory, and digital-ethics perspectives, the framework presents a shift from restrictive, detection-oriented assessment cultures toward discernment, transparency, and responsible AI engagement. Across the literature reviewed, three principles consistently emerged as critical pillars for AI-resilient assessment practices:

1. Transparency: making AI use explicit through clear guidelines, declarations, and modelling ethical use
2. Reflection: requiring learners to demonstrate metacognitive engagement and critique AI outputs, a necessity in self-directed ODL learning
3. Authenticity: designing tasks rooted in context, personal judgement, and real-world complexity, which reinforces human agency and reduces the risk of AI-generated work

These principles are supported by institutional enablers, including ethical AI policies, tutor training, and AI literacy initiatives that ensure consistent and equitable implementation across distributed ODL environments. Together, they offer a cohesive and future-oriented approach for sustaining academic integrity while leveraging AI as a catalyst for deeper learning, creativity, and learner autonomy.

Limitations

Although the AI-Resilient Assessment Framework (ARAF) offers a theoretically grounded and future-oriented model for assessment in ODL, several limitations must be acknowledged. First, the framework is conceptual, developed through synthesis of existing literature rather than empirical testing. As such, its assumptions about learner agency, AI literacy, and metacognitive engagement remain theoretically plausible but unverified in real instructional settings. The rapid evolution of generative AI also means that conceptual models risk becoming outdated unless continuously revisited and refined.

A second limitation concerns the variability of institutional capacity across ODL providers. ODL institutions differ widely in terms of technological infrastructure, policy maturity, human resources, and readiness for AI adoption. While ARAF presupposes the availability of AI literacy training, ethical guidelines, and educator professional development, some institutions, particularly those in resource-constrained contexts, may lack the structural support necessary to implement these components effectively. This may result in uneven adoption of the framework and inconsistent learner experiences.

A third limitation relates to the diversity of ODL learners. ODL cohorts typically comprise working adults, individuals from varied socio-economic backgrounds, and learners with differing levels of digital literacy. While ARAF assumes a degree of self-regulation and reflective capacity, not all learners may be equally prepared to critique AI outputs or document their interactions through reflective artefacts. For learners with weaker digital skills or limited access to stable internet and devices, reflective logs or AI-based tasks may unintentionally increase cognitive and technological burden.

Additionally, ethical and data-privacy concerns constrain the applicability of certain AI tools within ODL. Many popular generative AI systems operate with opaque data governance models, potentially exposing students' prompts, drafts, or personal information to third-party platforms. For ODL institutions operating across borders, conflicting data-protection regulations further complicate the development of unified AI-use policies. As ARAF encourages transparency in documenting AI interactions, institutional approval and compliance with privacy standards become essential but challenging.

Finally, the current body of literature offers limited comparative frameworks against which ARAF can be benchmarked. Most existing research discusses AI-integrated assessment in general higher education contexts, with fewer studies focusing specifically on ODL environments. This restricts triangulation of ideas and limits the robustness of conceptual validation. Therefore, while ARAF provides a timely response to emerging challenges, its generalisability and practical applicability require systematic empirical investigation.

Direction of Future Research

Several research opportunities emerge from the development of ARAF, particularly in validating its relevance and effectiveness within ODL environments. Future work should focus on empirical studies that examine how transparency, reflection, and authenticity manifest in real assessment tasks supported by generative AI. Such research may explore learner engagement, tutor workload, academic integrity outcomes, and the depth of metacognitive reasoning demonstrated in AI-assisted assignments. Mixed-methods approaches are likely to be especially valuable, as they can capture the complexity of learner experiences and the nuances of human–AI interaction.

Further research is also needed to understand how ARAF operates across different academic disciplines. Assessment authenticity and reflective requirements may vary substantially between fields such as engineering, business, education, or the humanities. Comparative studies could reveal discipline-specific adaptations necessary to optimise AI-resilient assessment design in ODL, strengthening the framework's versatility and practical utility.

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Longitudinal research represents another meaningful direction. Because ODL learners often study independently and across extended time frames, it would be beneficial to investigate whether sustained exposure to ARAF-based practices strengthens AI literacy, ethical reasoning, and learner autonomy over time. Such studies would provide insight into whether ARAF promotes enduring developmental outcomes rather than short-term compliance with assessment expectations.

There is also substantial potential for research into technological innovations that operationalise ARAF within virtual learning environments. This includes the development of LMS-integrated reflection tools, automated prompt logs, AI-assisted drafting spaces with transparency features, and digital dashboards that support both learners and educators in monitoring AI engagement. These tools may help scale ARAF implementation across large ODL cohorts.

Equity- and inclusivity-oriented research is equally critical. Since ODL cohorts are highly diverse, future studies should investigate whether ARAF disproportionately benefits or disadvantages particular learner groups based on digital access, prior AI experience, or linguistic background. Understanding these dynamics will be essential for ensuring that AI-resilient assessment strengthens not undermines ODL's mission of widening participation and promoting lifelong learning.

Finally, research on governance and institutional policy is urgently needed. As ODL institutions begin formalising AI-use regulations, studies examining policy effectiveness, institutional readiness, educator perceptions, and student compliance will offer insights into how governance frameworks can best support ethical, scalable, and sustainable AI integration.

Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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