International Journal of Learning, Teaching and Educational Research
Vol. 25, No. 2, pp. 742-762, February 2026
https://doi.org/10.26803/ijlter.25.2.33
Received Oct 25, 2025; Revised Dec 29, 2025; Accepted Feb 9, 2026

Cultivating Responsible AI Use through Formative Assessment: Insights from ODeL Mathematics Students

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Abstract. This study examined how open distance e-learning (ODeL) mathematics students engage with generative artificial intelligence (GenAI) tools within a formative assessment context, focusing on the extent to which their practices reflect responsible, reflective, and ethically aligned use. Guided by the aim of understanding students' GenAI literacy and the learning conditions that shape literacy, the study employed a qualitative descriptive design supported by limited quantitative frequency data from an online questionnaire. The three themes that emerged were uneven familiarity with GenAI tools; defensive and strategic paraphrasing behaviours shaped by institutional messaging and assessment pressures; and the role of formative feedback in promoting ethical engagement. While most students showed conceptual awareness of GenAI's capabilities and limitations, it was confidence levels, not fear of detection, that strongly influenced their practices. These findings highlight the need for assessment designs that foreground transparency, metacognitive reflection, and scaffolded development of artificial intelligence literacy, rather than punitive or compliance-oriented approaches. The study contributes to the growing literature on artificial intelligence in higher education by providing an empirical account of GenAI literacy in an open distance e-learning mathematics context within the Global South. It also offers practical implications for lecturers seeking to integrate AI responsibly into formative assessments while maintaining academic integrity and supporting student learning.

Keywords: Artificial intelligence literacy; formative assessment; academic integrity; mathematics education; open distance e-learning

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1. Introduction

Artificial intelligence (AI) literacy in higher education is increasingly understood as a teachable, staged, and context-dependent capability rather than a diffuse digital aptitude. Almatrafi et al. (2024) characterised literacy as comprising interrelated elements of conceptual understanding, application, evaluation, and ethics, while Long and Magerko (2020) and Zhou and Schofield (2024) outlined how students progress across these dimensions in authentic academic tasks. When viewed through a formative assessment lens, the pedagogical implications become clearer. Sadler (1989) argued that improvement hinges on students understanding standards, comparing their current work with those standards, and acting to close identified gaps. Subsequent work by Black and Wiliam (1998) and Carless and Boud (2018) showed that explicit intentions, transparent exemplars, and feedback designed for uptake cultivate the evaluative judgement needed to determine when to trust, adapt, or reject AI-generated outputs.

These imperatives take on particular significance in mathematics education. The field has seen rapid expansion in intelligent tutoring systems, adaptive technologies, and, more recently, classroom uses of generative tools. However, ethical concerns, uneven teacher preparedness, and persistent inequities remain. Nguyen and Pham's (2025) decade-long mapping highlights how these issues shape implementation and student outcomes. Integrity research echoes these findings; detection mechanisms alone do not reliably influence behaviour.

Instead, capability, clarity of expectations, and structured rehearsal of responsible practice are more influential, as demonstrated by Bittle and El-Gayar (2025) and supported by programme-level evidence favouring explicit modelling and guided practice over deterrence (Sefcik et al., 2020). Policy debates reinforce this direction; UNESCO's recommendations emphasise human agency, transparency, and accountability, requiring institutions to educate for judgement rather than outsource it to automated tools (Ramos et al., 2024).

Context amplifies these concerns within open distance and e-learning (ODeL). Zawacki-Richter and Naidu (2016) showed that access, isolation, and institutional support strongly shape online participation. In South Africa, evidence from emergency remote teaching underscored how digital inequalities affect first-generation and rural students, with effects that endure beyond a crisis (Czerniewicz et al., 2020; Mhlanga & Moloi, 2020). Recent work also foregrounds disability, illustrating how institutional design determines whether students can participate on equitable terms in digital higher education (Zongozzi & Ngubane, 2025). Under such conditions, misconceptions about AI do not dissipate through incidental use; they accumulate.

For ODeL specifically, literacy-orientated teaching and flexible support pathways function as both pedagogical and equity commitments. During the study period, the South African ODeL institution of the study introduced a compulsory academic integrity course for all National Qualifications Framework 5–8 students, which included practical guidance on ethical AI use. This situated the study's

cohort within a broader transition from deterrence to educative integrity (UNISA, 2025).

Despite the rapid uptake of generative tools and the proliferation of AI literacy frameworks, a specific empirical gap remains. Little research systematically documents ODeL students' pre-intervention AI literacy in mathematics education—particularly their mental models of how AI works, their assessment-specific practices, and their articulated support needs in a South African public university. Existing contributions have tended to emphasise policy, detection, or general digital literacies and rarely triangulate real assessment episodes with cohort-wide diagnostic evidence to inform the design of formative, integrity-supportive teaching.

Institutional analyses sharpen this gap. Ngoveni (2025a) showed that ambiguous communication and limited practice-orientated guidance foster defensive paraphrasing rather than confident engagement with AI. A companion article argued that the question is not whether AI belongs in mathematics education, but how to integrate it responsibly with explicit attention to verification, explanation, and attribution in assessed tasks (Ngoveni, 2025b). The immediate impetus for this study originated from the initial essay-type assignment in a mathematics education module, wherein numerous submissions exhibited improper AI utilization in accordance with institutional directives. The pattern revealed reliance without understanding, compliance-driven paraphrasing, and uncertainty about acceptable practices. Without a data-led profile of students' AI literacy and preferred modes of support, the institution lacks an evidence base for designing formative interventions that both uphold integrity and build capability.

This study is grounded in Zhou and Schofield's (2024) AI literacy framework and the formative assessment theory, as articulated by Sadler (1989), Black and Wiliam (1998), and Carless and Boud (2018). These frameworks informed the instrument design, coding approach, and derivation of the research questions. Guided by these lenses, the study addressed three questions:

RQ1: How do students describe their familiarity with AI tools, and what do they believe these tools are doing when generating text for academic work?

RQ2: How are students currently using AI in assessment settings, and are these practices driven more by understanding or by compliance-orientated strategies?

RQ3: What forms of instruction, resources, and feedback do students say they need to engage with AI ethically and confidently in an ODeL environment?

The study's contribution is threefold. First, it offers an empirically grounded account of students' pre-intervention perceptions in a large ODeL mathematics education cohort. Second, it advances the argument that AI literacy is best cultivated within a formative assessment ecology that builds evaluative judgement rather than outsourcing it to detection technologies. Third, it provides new cohort-level evidence demonstrating that a shift from punitive policing to

formative support is not only desirable in principle but precisely aligned with students' articulated needs.

1.1 Theoretical Framework

This study was anchored in a dual theoretical framing that integrated Zhou and Schofield's (2024) generative artificial intelligence (GenAI) literacy framework with the formative assessment theory as articulated by Sadler (1989), and later expanded by Black and Wiliam (1998). Together, these perspectives provided complementary lenses for understanding how students in an ODeL mathematics education context engage with generative GenAI, how their literacy develops, and what pedagogical structures are needed to support responsible and confident use.

Zhou and Schofield (2024) conceptualised GenAI literacy as a multidimensional capability encompassing four interrelated domains: knowing and understanding AI, applying AI in practice, evaluating and creating with AI, and acting ethically. This framework moves beyond digital competence to foreground critical and ethical dimensions of engagement: what students understand about GenAI; how they use it; how they judge its outputs; and how they exercise responsibility in doing so. In the present study, these dimensions provided a structured interpretive lens for examining students' uneven familiarity with GenAI tools, their misconceptions about how such systems operate, and their compliance-driven practices, such as defensive paraphrasing or avoidance behaviour. The framework thus illuminated where students were situated developmentally within the broader continuum of GenAI literacy and which aspects required targeted instructional support.

The formative assessment theory provided the pedagogical grounding for interpreting students' expressed needs for clearer guidance, training, and feedback. Sadler (1989) proposed that meaningful improvement depends on students' ability to understand standards of quality, compare their current work to those standards, and take purposeful action to close any gaps. Building on this foundation, Black and Wiliam (1998) demonstrated that when learning intentions are explicit, exemplars make quality visible, and feedback is timely and usable, students develop evaluative judgment—the capacity to regulate their learning. Within the context of GenAI, these principles translate into helping students not only use tools but also interrogate, verify, and justify their outputs through iterative feedback processes.

Integrating these frameworks, the study conceptualises GenAI literacy as a formative and developmental process rather than a static skill set. Students' reliance on tools without understanding, compliance to guidelines without confidence, and aspirations without support illustrate a literacy gap that must be addressed through deliberate scaffolding involving modelling, dialogue, and feedback to make responsible GenAI use both teachable and assessable. This theoretical alignment shifts the focus of academic integrity from enforcement to education, framing GenAI engagement as both a pedagogical opportunity and an ethical practice. The combined literacy formative lens provides a practical manner for designing equitable, capability-based approaches to GenAI in higher

education, especially in ODeL contexts in which isolation and digital inequality amplify misunderstanding.

2. Literature Review

2.1 AI Literacy as a Teachable, Situated Competence

Examining literacy first, rather than regulation, shifts the question from "*How do we police AI?*" to "*What do students need to use AI responsibly?*" Holbeck (2025) argued that higher education should move beyond detection toward cultivating AI literacy that enables students to make ethical, informed choices about generative technologies. AI-literacy scholarship responds directly to this challenge. Long and Magerko (2020) identified competencies such as understanding how models generate text, recognising limitations and biases, and knowing when and how to employ AI in disciplinary tasks. Zhou and Schofield (2024) adapted this framework for higher education, delineating four interrelated dimensions: comprehending AI, utilising AI, evaluating and creating with AI, and acting ethically.

Without explicit demystification, students frequently form inaccurate mental models—treating generative systems as search engines or over-trusting their fluency (Busch et al., 2023; Solyst et al., 2024). UNESCO's recommendation similarly emphasises human agency, transparency, and accountability, implying that literacy must be embedded within curricula, rather than outsourced to detection technologies (Allahrakha, 2024). Recent ODeL studies reinforce this position, showing that defensive paraphrasing flourishes when clarity and guidance are limited, indicating the importance of visible, discussable, and scaffolded AI use in mathematics education (Ngoveni, 2025a, 2025b).

2.2 Formative Assessment, Feedback Literacy, and Evaluative Judgement

The pedagogical mechanism of formative assessment facilitates the development of AI literacy. Sadler (1989) maintained that improvement depends on students understanding standards, comparing their work to those standards, and taking informed action to close identified gaps. Black and Wiliam (1998) demonstrated that clarifying intentions, eliciting evidence of learning, and providing actionable feedback significantly enhance achievement. Subsequent design-oriented scholarship emphasises self-regulation and feedback usability in practice (Boud & Molloy, 2012; Nicol & Macfarlane-Dick, 2006).

Carless and Boud (2018) presented the concept of feedback literacy, which encompasses the skills required for students to seek, interpret, and utilize feedback. Concurrently, Winstone and Carless (2019) emphasised the necessity for cultures that facilitate the acceptance of feedback. In AI-rich learning environments, these principles point to the value of helping students interrogate AI outputs, justify their trust or scepticism, and incorporate paraphrasing, verification, and citation transparently. Without such structures, students often default to compliance behaviours rather than confident evaluative judgement.

2.3 Integrity as Education Rather Than Enforcement

Academic integrity research has shifted from a policing paradigm to an educative one. Bertram Gallant (2017) conceptualised integrity as a teaching-and-learning responsibility, whereby institutions cultivate students' ethical capability rather than relying primarily on deterrence. Curriculum-embedded integrity education has been shown to reduce breaches more effectively than punitive signalling, particularly when instruction includes explicit modelling and guided practice (Sefcik et al., 2020). Studies of contract cheating similarly warn that punitive-only strategies may displace misconduct rather than reduce it if assessment design remains unchanged (Bretag et al., 2018). When considered alongside findings in ODeL contexts, paraphrasing merely to avoid penalties signals insufficient pedagogy rather than moral failure.

2.4 ODeL Realities and Digital Inequalities

Context fundamentally shapes AI engagement, and the ODeL environment amplifies these effects. Research indicates that disparities in device access, bandwidth limitations, and social isolation constrain spontaneous clarification opportunities and exacerbate misunderstanding (Zawacki-Richter & Naidu, 2016). South African studies about the COVID-19 crisis, which brought about the transition to online-learning, illustrate how digital inequalities influence participation and performance, especially for first-generation and rural students, with effects persisting into subsequent academic years (Czerniewicz et al., 2020; Mhlanga & Moloi, 2020).

More recent work foregrounds disability, demonstrating that inclusive institutional design determines whether students can engage equitably in digital higher education (Zongozzi & Ngubane, 2025). Under such conditions, misconceptions about AI accumulate rather than self-correct. ODeL therefore requires explicit demystification of generative systems and flexible, asynchronously accessible resource pathways, such as short instructional videos, annotated exemplars, and structured discussion spaces. This aligns with recent research framing AI literacy not only as a pedagogical aim but as an equity imperative (Ngoveni, 2025a, 2025b).

2.5 AI in Mathematics Education as a Test for Pedagogy

Mathematics is procedurally dense, feedback-intensive, and highly vulnerable to answer-seeking that circumvents reasoning. Nguyen and Pham (2025) mapped a decade of AI integration in mathematics education, noting rapid expansion in intelligent tutoring, adaptive systems, and generative tool use, alongside persistent challenges relating to ethics, teacher preparedness, and equitable access. Their synthesis suggests that technological adoption is outpacing pedagogical capacity. The present study extends this work by providing empirically grounded insight into what students understand, fear, and request in relation to GenAI, particularly within the structural realities of distance learning.

2.6 Synthesis and Design Stances for the Present Study

Across these themes, a coherent stance emerges. AI literacy is teachable and must be developed with attention to conceptual understanding, evaluation, ethics, and application (Long & Magerko, 2020; Zhou & Schofield, 2024). Formative

assessment offers the mechanism for this development by clarifying intentions, employing exemplars, structuring feedback for uptake, and building evaluative judgement so that students engage with AI as a partner in reasoning rather than a shortcut (Black & Wiliam, 1998; Carless & Boud, 2018; Sadler, 1989). In ODeL environments, design considerations must accommodate variable access and provide multiple pathways to learning (Zawacki-Richter & Naidu, 2016).

The empirical foundation presented in this study reinforces these claims: students report reliance without understanding, compliance without confidence, and a strong need for structured support. Collectively, the literature positions the shift from punitive policing to formative, literacy-oriented teaching as both pedagogically necessary and practically responsive to students' articulated needs.

3. Methodology

3.1 Research Design and Paradigm

This study adopted a qualitative-dominant exploratory mixed-methods design situated within an interpretive paradigm. The primary aim was to develop an in-depth understanding of how ODeL mathematics education students perceive, use, and make sense of GenAI in assessment contexts. Although the focus of the study was qualitative, limited quantitative data drawn from closed-ended survey items were incorporated to provide contextual descriptive patterns. This positions the design as qualitative led, rather than purely qualitative, resolving potential contradictions between design and instrumentation.

The interpretive paradigm assumes that knowledge is co-constructed through participants' subjective experiences and meanings, making it well suited to surfacing students' mental models, uncertainties, and developmental needs regarding emerging technologies in higher education (Creswell & Poth, 2016). This approach aligns with the dual theoretical framing of GenAI literacy (Zhou & Schofield, 2024) and the formative assessment theory (Sadler, 1989; Black & Wiliam, 1998), both of which foreground meaning-making, judgement, and developmental progression. The design therefore supported the generation of rich, contextualised insights, which would not be accessible through a purely positivist or measurement-oriented approach.

3.2 Context of the Study

The research was conducted at a large South African ODeL institution characterised by geographically dispersed students, varying digital access, and limited informal peer interaction. Such contextual conditions shape how students encounter and integrate GenAI into their academic practices. The selected undergraduate mathematics education module requires written, conceptual, and reflective assignments, providing an authentic site for exploring assessment-related decisions involving GenAI.

3.3 Participants and Sampling

The participants were 342 students enrolled in the undergraduate mathematics education module, representing 77.2% of the full cohort (n = 443). Purposive and convenience sampling were used. Purposive sampling was appropriate because

the study targeted students engaged in assessment tasks in which GenAI use was directly relevant. Convenience sampling reflected the practical distribution of the online survey to all students registered on the module's learning management system. Although the sample is large for qualitative research, it is suitable for this study's qualitative-dominant exploratory mixed-methods design, which aimed to identify cohort-level patterns in GenAI literacy rather than conduct in-depth individual case analysis. The diversity of the participants enhanced the credibility and transferability of the findings. Participation was voluntary. The survey instrument is provided in Appendix 1.

3.4 Data Collection

Data were collected through an online survey comprising both closed-ended and open-ended items. The closed-ended questions captured descriptive patterns such as students' familiarity with GenAI tools, frequency of use, and types of platforms with which they engaged (such as ChatGPT, Gemini, Grammarly). These items served a contextualising rather than inferential purpose.

The open-ended questions elicited richer accounts of students' conceptual understanding of GenAI (e.g., how they believed the systems generate outputs), perceptions of appropriate and inappropriate use, motivations for engagement, concerns about penalties or misuse, and their preferred forms of institutional support. The instrument also invited students to propose training, resources, or pedagogical practices that would strengthen their ability to engage ethically and confidently with GenAI in an ODeL context. The survey was administered via the university's learning management system and remained open for three weeks to accommodate asynchronous participation. Responses were automatically anonymised and required approximately 15–20 minutes to complete.

3.5 Data Analysis

The study employed reflexive thematic analysis (RTA), as articulated by Braun and Clarke (2019), an approach that recognises a researcher's active and interpretive role in meaning-making. Rather than aiming for objectivity or coding reliability, RTA treats the researcher's subjectivity as a valuable analytic resource through which knowledge is co-constructed with the data. Analysis was therefore conceptualised as an active, generative, and creative process, which prioritised interpretive depth and theoretical transparency over procedural uniformity.

Consistent with this orientation, the researcher engaged in deep familiarisation with the participants' responses through repeated reading and reflective notetaking. Coding proceeded in a fluid, recursive manner, capturing patterns of meaning related to students' conceptual understanding of GenAI, their motivations for use, and their expressed support needs. These codes were iteratively refined into themes, conceptualised as patterns of shared meaning unified by central organising concepts rather than as summaries of surface-level topics.

The analytic process was documented through reflexive journaling, which traced interpretive decisions, theoretical assumptions, and shifts in understanding over time. This process led to the development of three main themes: reliance without

understanding, which refers to students' uneven familiarity with GenAI tools and limited understanding of how they work; compliance without confidence, which highlights defensive and risk-averse usage shaped by unclear institutional boundaries; and aspiration without support, which reflects explicit calls for training, guidance, and accessible learning resources.

Descriptive statistics drawn from closed-ended survey items were used solely to contextualise these qualitative findings; for instance, to indicate which GenAI tools were most frequently used and how many students reported complete unfamiliarity. The RTA process and contextual descriptive evidence provided a coherent interpretive literacy profile of the ODeL mathematics student cohort, situated within the study's dual theoretical framing of GenAI literacy (Zhou & Schofield, 2024) and the formative assessment theory (Black & Wiliam, 1998; Sadler, 1989).

3.6 Trustworthiness and Reflexivity

To ensure the trustworthiness of the study, the criteria proposed by Lincoln and Guba (1985), of credibility, dependability, transferability, and confirmability, were systematically applied. Credibility was strengthened through the triangulation of data sources, drawing on both open-ended and closed-ended survey responses, and through prolonged engagement with the data during iterative coding and analysis. Dependability was maintained by keeping a detailed audit trail that documented coding decisions, thematic refinements, and analytic shifts over time, ensuring transparency in the research process. Transferability was supported by providing an abundant description of the ODeL context, enabling readers to determine the relevance of the findings to comparable institutional and disciplinary settings.

Finally, confirmability was reinforced through ongoing reflexive journaling, which helped the researcher remain critically aware of potential biases arising from their dual role as lecturer and investigator. This reflexive practice ensured that interpretation remained grounded in participants' voices, privileging their lived experiences and meanings over researcher assumptions (Berger, 2015).

3.7 Ethical Considerations

The Institution's Ethics Review Committee (ERC Reference Number: 7209) granted ethical clearance for the study. The participants were informed of the study's purpose, assured of voluntary participation, and reminded that non-participation would not affect their academic standing. Informed consent was obtained electronically prior to survey access. All data were stored securely in password-protected institutional servers and will be retained for fifteen years in line with university policy.

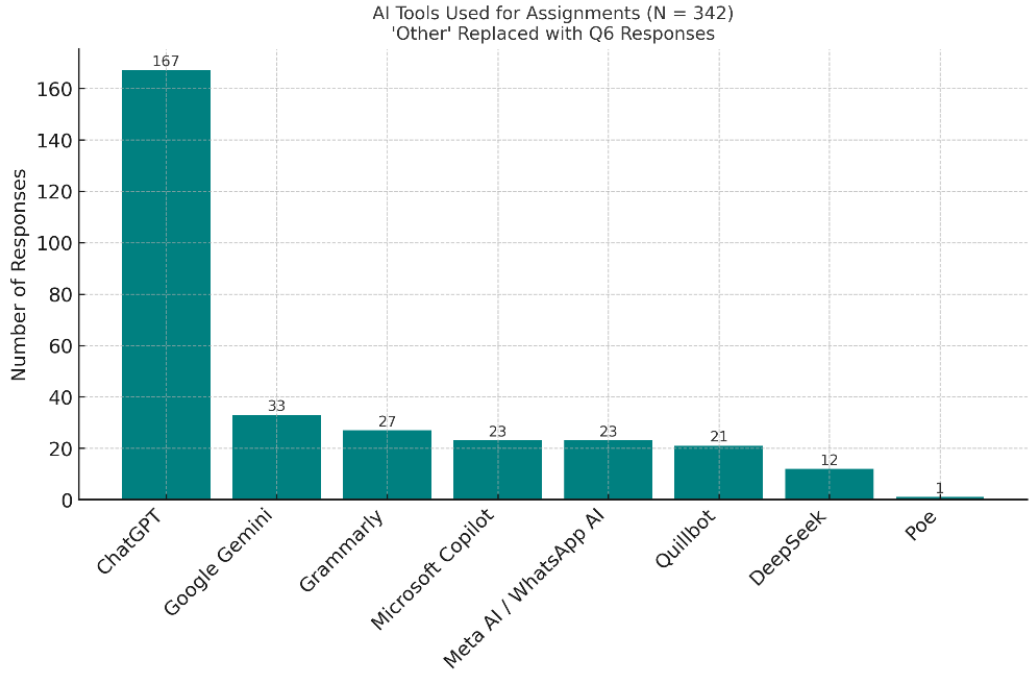
4. Findings

This section presents the findings generated through reflexive thematic analysis. The three overarching themes—*reliance without understanding, compliance without confidence, and aspiration without support*—capture how students described their familiarity with GenAI tools, their beliefs about how these systems work, their

patterns of use in assessment contexts, and the kinds of support they require to engage ethically and confidently in an ODeL mathematics education environment. These themes reflect students' developmental positioning within the GenAI literacy framework and synthesise patterns of meaning across the cohort.

4.1 Theme 1: Reliance without Understanding—Students' Familiarity and Mental Models of GenAI

To contextualise the qualitative findings, students first indicated which GenAI tools with which they were familiar through a closed-ended survey item (see Figure 1). These self-reported frequencies show that ChatGPT dominated tool use at 49% (n = 167), followed by Google Gemini (10%), Grammarly (8%), Microsoft Copilot (7%), Meta AI and WhatsApp AI (7%), QuillBot (6%), DeepSeek (4%), and Poe (1%).



Note. Percentages are descriptive and used solely to contextualise qualitative findings

Figure 1: Contextual data on GenAI tools used for assignments among ODeL mathematics education students (N = 342)

The students' responses showed that many equated AI primarily with ChatGPT, indicating narrow engagement with the broader GenAI landscape. Comments such as "*ChatGPT is the one I know because everyone talks about it*" and "*I only use ChatGPT, nothing else*" illustrate this strong platform-specific association. By contrast, a notable proportion of participants reported unfamiliarity or complete non-use, stating "*I don't know any of these tools*" and "*I am not familiar with ChatGPT*." These admissions were often accompanied by feelings of exclusion or digital inequality, reflected in statements such as "*Others in my class know these things, but I don't even know where to start.*"

Together, these responses depict a fragmented cohort comprising confident adopters, tentative experimenters, and disconnected students, reinforcing the persistence of digital inequalities characteristic of ODeL contexts. Students' explanations of how GenAI systems work revealed similarly uneven literacy. While some described basic functioning, others articulated deep uncertainty or misconceptions, highlighting a broader conceptual gap in understanding how generative models produce text and where their limitations lie.

A dominant view was that GenAI acted as an automated source of answers, with students remarking that "*They grab information off the internet*" or "*It helps with the answers I need.*" Some acknowledged potential flaws, noting "*They are programmed to generate answers, even if sometimes incorrect.*" These explanations show a utilitarian orientation focused on output acquisition rather than conceptual understanding. In contrast, other students described GenAI as a clarifying tool that helped them interpret academic expectations. Statements such as "*They make me understand what is wanted from an assessment*" and "*It explains the questions in a way I can understand*" portray GenAI as a mediator that makes assessment tasks more accessible.

However, many students openly expressed confusion, noting "*I don't know how it works*" or "*I have no idea,*" revealing fragile conceptual foundations and reliance on GenAI despite limited understanding. Collectively, these insights constitute the theme reliance without understanding, corresponding to the foundational dimension of knowing and understanding AI within Zhou and Schofield's (2024) GenAI literacy framework.

4.2 Theme 2: Compliance without Confidence — Students' AI Use in Assessment Contexts

The second theme, compliance without confidence, captured how students described using GenAI in assessment contexts. Their engagement was shaped less by confidence or literacy and more by uncertainty, caution, and fear of penalties. Some students used GenAI to generate assignment content quickly, explaining "*It helps with the answers I need*" and "*I ask it for the answer and then I rewrite it.*" Such shortcut-oriented use reflects instrumental engagement aimed at completing tasks efficiently, often without evaluating accuracy or relevance. Others adopted a more reflective approach, using GenAI to unpack assessment expectations. Comments such as "*It makes me understand what is wanted*" and "*It explains the questions in a way I can understand*" suggest emerging literacy in which GenAI supports comprehension rather than merely producing outputs.

A striking and consistent pattern, however, was compliance-driven paraphrasing motivated by fear of misconduct. Students reported altering GenAI-generated text primarily to avoid penalties: "*It gives us all the same answers, so I paraphrase to make it my own words*" and "*I paraphrase so it's not plagiarism.*" These comments illustrate that students policed their usage in the absence of clear, supportive guidance. Some students used GenAI despite limited understanding, noting "*I don't know how it works but I still try it for answers,*" revealing risk-averse behaviour shaped by uncertainty rather than reflective judgement. This theme aligns with the ethical and evaluative dimensions of the GenAI literacy framework, showing that

students lacked evaluative confidence, often engaging with GenAI defensively instead of developmentally.

4.3 Aspiration Without Support—Students' Desired Instruction, Guidance, and Resources

The third theme, aspiration without support, synthesises students' strong desire for structured instructional guidance. While students were willing to engage with GenAI, they emphasised that they lacked the training and scaffolding needed to do so ethically and effectively. Many explicitly requested formal instructions on GenAI use, stating "*We need training on how to use AI correctly*" and "*They should show us how to use ChatGPT for assignments.*" Students also highlighted the need for clear, accessible guidelines on acceptable and unacceptable AI use, explaining "*Examples of what is allowed would help*" and "*Clear rules for using AI in assignments would help us feel safe.*"

Such ambiguity contributed to compliance-driven behaviours observed earlier. Students further expressed a need for modelling and feedback to support responsible use, requesting "*Show us how to reference AI correctly*" and "*Lecturers should demonstrate acceptable and unacceptable use.*" These comments demonstrate alignment with formative assessment principles centred on transparency, exemplars, and actionable feedback.

Finally, students described ODeL-specific support needs arising from limited real-time interaction, explaining "*We need step-by-step videos*" and "*We don't have someone to ask questions.*" This points to the necessity of multimodal, flexible resources that accommodate diverse levels of digital readiness. This theme reflects the application dimension of the GenAI literacy framework, showing that students are prepared to develop their literacy if institutional structures are in place.

Across these three themes, a coherent literacy profile emerges. Students showed high functional reliance on GenAI tools but low conceptual understanding of how they operate. Their engagement was often shaped by fear of penalties, uncertainty, and a lack of clear guidance, resulting in compliance-driven practices rather than confident, reflective use. At the same time, students strongly desired structured training, clear guidelines, and formative instructional support that would enable them to navigate GenAI tools ethically and confidently. These findings revealed a incongruity between students' willingness to engage with GenAI and the limited pedagogical structures available to scaffold their development, which pointed to the importance of deliberate, feedback-rich interventions that build conceptual understanding, evaluative judgement, and ethical competence—especially in ODeL mathematics education contexts in which digital inequalities amplify existing challenges.

5. Discussion

The two interpretive lenses that guided this analysis were Zhou and Schofield's (2024) AI literacy framework and the formative assessment theory, as articulated by Sadler (1989) and expanded by Black and Wiliam (1998). Together, these

frameworks illuminated how students' engagement with GenAI reflects staged literacy development and the pedagogical need for formative structures that make responsible use teachable, visible, and assessable. The findings portray a cohort negotiating GenAI in a landscape marked by enthusiasm, uncertainty, defensive strategies, and strong demands for guidance. Rather than rejecting GenAI, students encountered it with curiosity but lacked the conceptual understanding and pedagogical support necessary for confident and ethical engagement.

5.1 Uneven Familiarity as a Staged Literacy Challenge

Students' uneven exposure to GenAI tools—dominated overwhelmingly by ChatGPT—illustrates how AI literacy develops in stages rather than emerging spontaneously. Some students used GenAI frequently, often equating it exclusively with a single branded interface, while others had never interacted with such tools. Within Zhou and Schofield's (2024) framework, these behaviours correspond to the earliest layers of literacy: knowing and applying, with far less evidence of evaluating or acting ethically. The persistence of misconceptions, such as viewing GenAI as a search engine or as a source that "*grabs answers from the internet*," aligns with studies showing that novice users often construct inaccurate mental models of AI systems (Solyst et al., 2024).

In ODeL environments, these misconceptions rarely correct themselves. Zawacki-Richter and Naidu (2016) noted that in distance education, it is the design of learning environments—rather than their intent—that determines students' learning opportunities. Without modelling, dialogue, or immediate clarification, students rely on incidental exposure, peer hearsay, or trial and error. Therefore, the findings point out the need for structured, scaffolded teaching that moves AI literacy from awareness toward reflective, evaluative, and ethical engagement.

5.2 Over trust, Compliance, and Defensive Practice

Students' descriptions of GenAI as an "*answer machine*" or as a straightforward clarifier reveal a dual pattern of overtrust and oversimplification. Many valued the fluency and convenience of GenAI outputs but lacked the evaluative strategies needed to verify accuracy or recognise hallucinations, a pattern widely observed in early encounters with AI tools (Busch et al., 2024; Solyst et al., 2024). Other students described paraphrasing GenAI-generated text solely to avoid misconduct penalties. This behaviour signals compliance rather than capability and reflects the institutional ambiguity surrounding acceptable AI use.

From a formative-assessment perspective, these findings signal the absence of essential pedagogical structures. Sadler (1989) and Carless and Boud (2018) emphasised that improvement depends on students' ability to interpret standards, judge quality, and close gaps. Without clear expectations, exemplars, or feedback processes, students resort to risk-averse practices rather than building evaluative judgement. In this sense, defensive paraphrasing is not a moral failure but a predictable response to unclear rules and insufficient instructional guidance.

5.3 Integrity as Education, Not Enforcement

Students' defensive stance resonates with a broader shift in integrity scholarship from detection to education. Bertram Gallant (2017) argued that integrity is best

developed through capability-building rather than surveillance. Paraphrasing to evade detection reflects institutional ambiguity, not ethical deficit. Empirical evidence supports this; curriculum-embedded integrity education—particularly when modelling ethical use and providing structured practice—reduces breaches more effectively than punitive approaches (Sefcik et al., 2020; Bittle & El-Gayar, 2025). In GenAI-rich environments, this means designing assignments and learning experiences that teach students how to make ethical decisions: acknowledging AI assistance, verifying claims, explaining how outputs were adapted, and understanding when AI should or should not be used. These practices align with the formative assessment theory, which frames learning as a process of comparing work to standards and taking action to improve (Black & Wiliam, 1998; Sadler, 1989).

Thus, this study extends formative-assessment scholarship by demonstrating that feedback processes can cultivate evaluative judgement and ethical reasoning in AI-supported learning, reframing integrity as a developmental process rather than a policing mechanism.

5.4 Feedback Literacy and the Design of Uptake

Students' repeated calls for "*clear guidelines*," "*training*," and "*step-by-step videos*" map closely onto the concept of feedback literacy—the capacity to seek, interpret, and use feedback for improvement (Carless & Boud, 2018; Winstone & Carless, 2019). Their responses indicate readiness rather than resistance: a willingness to learn responsible GenAI use if given explicit support. In ODeL contexts, in which isolation and uneven connectivity limit spontaneous clarification, multimodal resources become crucial pedagogical infrastructure. Videos, annotated exemplars, and AI-use checklists can function as asynchronous feedback mechanisms, enabling students to practice responsible engagement even in the absence of real-time lecturer interaction. As Zawacki-Richter and Naidu (2016) emphasised, well-designed distance learning environments can compensate for the absence of immediate, interpersonal feedback by embedding support directly into learning materials.

5.5 Equity and the ODeL Context

The patterns observed in this study are pedagogical, but they are also structural. Inequities in access—such as bandwidth constraints, limited device availability, disability-related barriers, and first-generation student status—shape who is able to engage meaningfully with GenAI and in what ways (Czerniewicz et al., 2020; Zongozzi & Ngubane, 2025). Students with limited access or exposure face increased risk of marginalisation as GenAI becomes more integrated into educational practices. For ODeL institutions, fostering GenAI literacy is therefore not only a matter of pedagogical design but also an equity imperative.

Low-bandwidth materials, alternative formats, mobile-friendly resources, and inclusive design are essential to avoid reinforcing or widening existing digital divides. These findings mirror patterns documented in South African ODeL research, in which digital inequality, access barriers, and institutional design significantly shape learning outcomes. This study contributes to that literature by demonstrating that GenAI engagement—without explicit teaching—may

reproduce these inequalities, creating new layers of exclusion even within technologically enabled systems.

5.6 Policy and Pedagogical Implications

At a policy level, UNESCO's recommendations emphasise human agency, transparency, and accountability in AI-supported education, underscoring the responsibility of institutions to cultivate judgement rather than outsource it to automated systems (Ramos et al., 2024). Practically, this entails embedding GenAI literacy within assessment design: specifying permissible uses in task briefs, providing exemplars that differentiate legitimate support from substitution, and assessing both processes and products through reflective artefacts (e.g., AI-use statements, verification notes). Through feedback-rich instructional design that promotes uptake, institutions can cultivate evaluative judgement: the capacity to determine when to trust, adapt, or reject GenAI outputs. This competence is fundamental to both formative assessment and ethical AI use, positioning literacy-building as essential to academic integrity and meaningful learning in GenAI-enabled education.

6. Conclusion

This study provided an in-depth qualitative exploration of how ODeL mathematics education students navigate generative GenAI within assessment contexts characterised by uncertainty, uneven access, and limited pedagogical guidance. The findings reveal three intersecting tensions—reliance without understanding, compliance without confidence, and aspiration without support—that shape students' engagement with GenAI tools. While some students used GenAI constructively to clarify instructions and enhance comprehension, many relied on defensive strategies or held inaccurate assumptions about how GenAI operates, revealing gaps in conceptual, ethical, and practical literacy. These patterns do not suggest resistance to GenAI but a clear need for structured guidance, ethical clarity, and scaffolded feedback to support responsible engagement.

Interpreted through Zhou and Schofield's (2024) AI literacy framework and the formative assessment theory (Black & Wiliam, 1998; Sadler, 1989), the findings extend pedagogical theorisation by demonstrating how feedback processes can develop both evaluative judgement and ethical reasoning in AI-mediated learning environments. In reframing academic integrity as a teachable capability rather than a compliance burden, the study positions formative assessment as a viable pedagogical route for cultivating responsible GenAI engagement. Through practice, modelling, and transparent design, AI literacy emerges not merely as a technical skill set but as a cognitive, ethical, and reflective learning outcome.

Contextually, the results strengthen existing research in ODeL on equity and digital inclusion (Czerniewicz et al., 2020; Zongozzi & Ngubane, 2025), highlighting how structural inequalities in access to bandwidth, devices, and institutional support shape students' capacity to develop GenAI literacy. Without intentional low-bandwidth and accessible learning design, AI-based pedagogies risk reinforcing existing disparities. Therefore, the findings underscore the

institutional imperative to embed AI literacy within curriculum and assessment — not as an optional digital enhancement but as an equity-driven capability essential to ethical, inclusive higher education. Collectively, the study calls for a shift from punitive to formative approaches in managing GenAI in ODeL contexts. Explicit instruction, visible exemplars, and feedback designed for uptake can foster the evaluative judgement necessary for students to engage critically, confidently, and responsibly with GenAI tools.

6.1 Limitations

This study offered a context-specific examination of GenAI literacy among mathematics education students at a South African ODeL institution, and its insights should be interpreted with this scope in mind. Students' experiences were influenced by disparate access to devices and bandwidth, differing levels of exposure to GenAI, and variations in academic preparedness, all of which may have affected their perceptions and reported practices. As a qualitative descriptive study, the analysis prioritised participants' accounts rather than behavioural verification or longitudinal tracking and therefore cannot capture changes in literacy development over time. The disciplinary focus on mathematics education may also limit transferability, as literacy trajectories and ethical challenges may differ across fields with distinct epistemic traditions. Despite these constraints, the findings provide a valuable diagnostic foundation for designing formative, feedback-rich interventions supporting responsible GenAI engagement in ODeL and similar distance-learning environments.

6.2 Recommendations

The findings highlight a clear institutional and pedagogical imperative: GenAI use should be taught as a literacy rather than policed as a rule. Institutions need to move beyond detection-focused responses and embed AI literacy within curriculum policy, assessment design, and everyday teaching practices. Formative AI literacy can be strengthened by designing assessment tasks that explicitly articulate permissible GenAI assistance, provide annotated exemplars which distinguish legitimate use from substitution, and assess processes, alongside products, through reflective components such as AI-use statements or verification notes. Lecturers require targeted professional development to enhance their feedback literacy for AI-integrated instruction, including strategies for modelling verification, attribution, and critical engagement with GenAI outputs in alignment with Zhou and Schofield's (2024) four dimensions of literacy which are knowing, applying, evaluating, and acting ethically.

Equitable and multimodal support resources are essential in ODeL contexts. Institutions should prioritise the creation of low-bandwidth, accessible learning materials (such as short instructional videos, citation and attribution templates, annotated examples, and asynchronous discussion spaces) that make responsible AI use transparent and revisitable for all students, including those facing connectivity or accessibility challenges. Academic integrity policies should adopt a developmental and human-centred orientation, using detection tools judiciously as diagnostic aids that prompt conversation about judgement, transparency, and accountability rather than as punitive mechanisms.

Finally, future research should explore how formative interventions influence students' evaluative judgement, ethical reasoning, and confidence over time and across diverse disciplinary and institutional contexts. Longitudinal and comparative studies can deepen understanding of how AI literacy develops and how feedback-based pedagogies can mitigate digital inequities while promoting ethical and responsible engagement with emerging technologies.

7. Conflict of Interest, Acknowledgements, and Related Declarations

7.1 Acknowledgments

The author extends sincere appreciation to the mathematics education students at the South African ODeL institution for their valuable participation in this study. Their openness and thoughtful reflections on the use of GenAI tools made this research possible. The author also acknowledges the institutional ethics committee for granting approval (ERC Reference Number: 7209), as well as colleagues and mentors who provided constructive feedback during the study design and manuscript development.

7.2 Author Contributions

The authors were responsible for all components of the study, including conceptualisation, research design, data collection, analysis, methodology development, interpretation, visualisation, and manuscript preparation. The authors independently managed the writing, review, and editing processes, ensuring the scholarly integrity and coherence of the final submission.

7.3 Competing Interests

The author declares no known competing financial or personal interests that could have influenced the conduct or outcomes of this research.

7.4 Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

7.5 Declaration of AI Use

Portions of this manuscript were prepared with the assistance of ChatGPT (OpenAI, GPT-5), which was used solely to support language editing, structural refinement, and improvement of clarity and conciseness. The authors verified all generated text for factual accuracy, academic integrity, and alignment with the study's findings and theoretical framework. The use of the tool did not influence data collection, analysis, or interpretation. Full responsibility for the content rests with the authors. QuillBot (premium) was employed solely for grammar and style refinement. Additionally, the authors reviewed, validated, and edited all sections of the final version of the manuscript and take full responsibility for its content and conclusions.

7.6 Data Availability

The datasets supporting this study's findings are available from the author upon reasonable request. In accordance with ethical requirements related to participant confidentiality and institutional approval procedures, raw qualitative data cannot

be publicly shared. However, anonymised excerpts may be made available for research verification purposes upon request.

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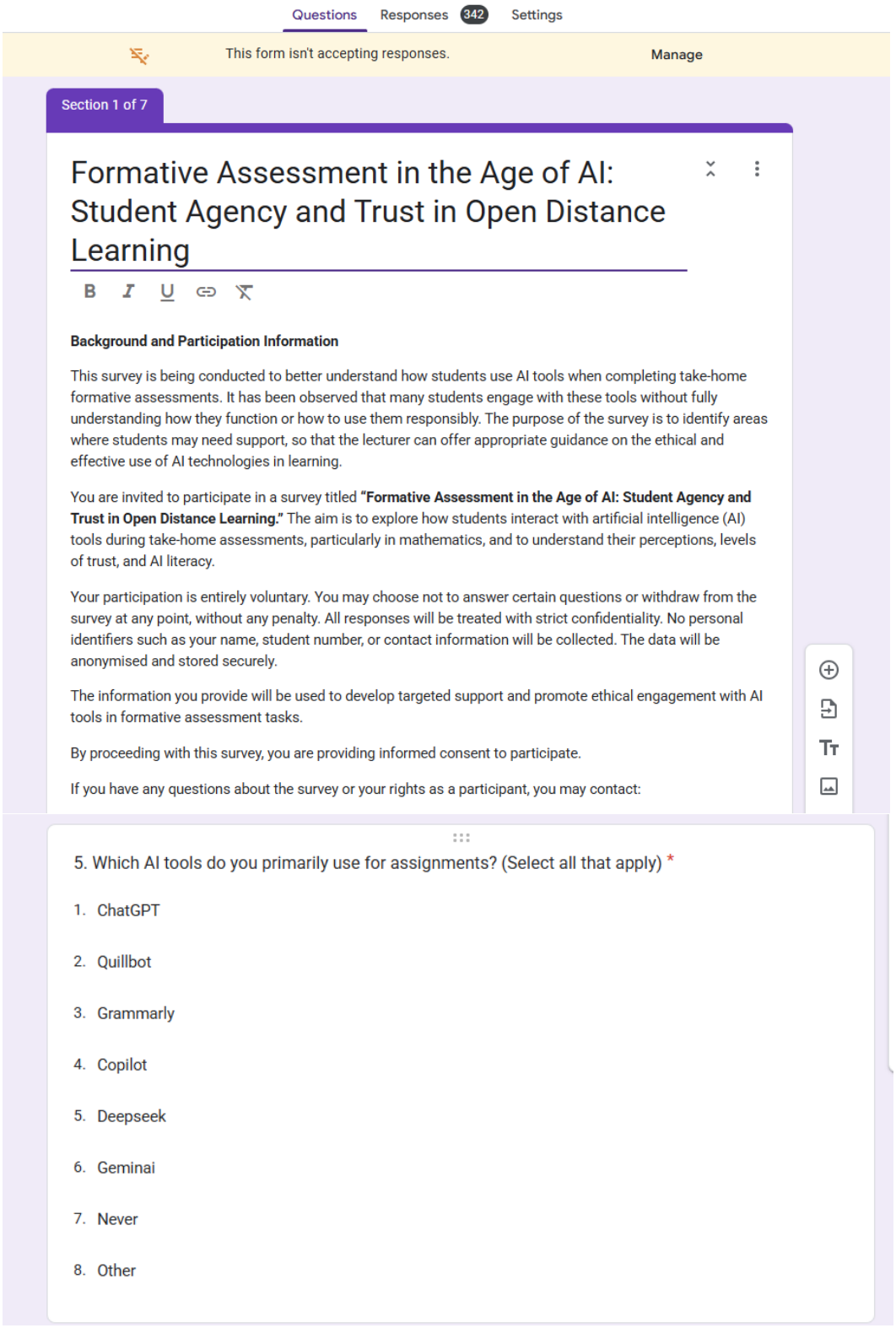
Appendix 1: Selected questions (relevant to the study) asked in the survey

Please note: Some information from the background and participation information has been redacted for the protection of the institution's anonymity.



6. If you selected "Other" to question 5, please provide our primary AI tool.

Short-answer text

20. In your experience, how has the use of AI tools affected your ability to complete mathematics assignments? *

Long-answer text

21. Describe any challenges you have faced when using AI tools to assist with take-home assessments. *

Long-answer text

22. What do you believe are the ethical responsibilities of students when using AI for assessments? *

Long-answer text

23. What kind of institutional guidance or support would help you use AI tools more responsibly and effectively? *

30. Can you explain how you think AI tools such as ChatGPT work when generating content for assignments?

Long-answer text

31. Describe how you learned about the AI tools you have used (e.g., through peers, social media, lecturers, formal training, etc.).

Long-answer text

32. What do you think are the limitations of using AI tools for mathematics tasks or assignments?

Long-answer text