Gray Areas and Alternative Resolutions on the Use of AI on Academic Assessments among ICT, TLE, and Language Educators

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ABSTRACT:

The expansion of generative artificial intelligence (GenAI), including large language models that produce text through probabilistic prediction and pattern recognition, has complicated conventional assumptions about authorship, originality, and academic integrity in educational assessment. While institutional discussions often focus on detection technologies, limited scholarship has examined how educators interpret and resolve ambiguous student AI use in actual classroom contexts. Anchored in Weick's Sensemaking Theory, this qualitative study examined how educators construct meaning around AI-related "gray areas" in assessment and how these interpretations shape instructional responses. Twenty (20) higher education educators from Information and Communications Technology (ICT), Technology and Livelihood Education (TLE), and Language disciplines in the Philippines participated in semi-structured interviews selected through purposive sampling. Ethical clearance was secured from the Institutional Review Board, and informed consent was obtained from all participants. Data were examined through Reflexive Thematic Analysis, involving iterative coding, reflexive journaling, peer debriefing, and thematic mapping to ensure

analytic transparency and coherence. The findings demonstrated that educators' interpretations were structured through three interconnected sensemaking processes: identity construction, enactment, and retrospection. Participants described tensions surrounding authorship verification, voice mismatch, process invisibility, and overreliance on AI detection tools. Rather than defaulting to surveillance-oriented enforcement, educators described adaptive strategies such as dialogic validation, staged drafting, oral defense, and contextual evaluation of learning evidence. This study advances a process-oriented explanation of how educators navigate AI-induced ambiguity in assessment settings. The integration of technological grounding with sensemaking constructs extends current discourse beyond descriptive concerns of misconduct and offers theoretically informed directions for institutional governance, professional development, and assessment redesign in AI-integrated academic environments.

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1. Introduction

The rapid integration of artificial intelligence (AI) into education has significantly transformed how teaching, learning, and assessment are conceptualized and enacted. Among the most disruptive developments is generative artificial intelligence (GenAI), including large language models (LLMs) and other probabilistic systems capable of producing human-like text, code, images, and structured outputs. These systems are trained on vast datasets and generate responses through predictive modeling rather than true comprehension, which may result in highly fluent outputs that contain inaccuracies, fabricated references, algorithmic bias, or "hallucinated" content. Alongside automated grading systems and intelligent tutoring applications, generative AI tools are now widely accessible to students and educators, reshaping academic production and evaluation practices. While these technologies offer increased efficiency, personalization, and innovation in assessment design, they simultaneously introduce epistemic and ethical ambiguities that challenge traditional assumptions about authorship, originality, competence, and fairness. The ability of AI systems to generate sophisticated outputs that mimic disciplinary conventions complicates judgments about student ownership and authentic learning. As AI continues to evolve, educational institutions worldwide face growing uncertainty regarding where to draw boundaries between acceptable assistance and academic misconduct, particularly in assessment contexts. For educators in disciplines such as Information and Communications Technology (ICT), Technology and Livelihood Education (TLE), and Language education, these tensions are especially pronounced because each field maintains distinct norms regarding technical proficiency, creativity, voice, and standards of originality [1- 4]

Although research on AI in education has expanded rapidly, much of the existing scholarship concentrates on student behavior, detection technologies, institutional governance frameworks, and risks of academic dishonesty [5]. Comparatively less attention has been devoted to the interpretive work undertaken by educators themselves when confronted with ambiguous AI-assisted submissions. This omission is significant because AI-related "gray areas" are not merely technical issues but socially constructed dilemmas requiring professional judgment. Educators function as gatekeepers of academic integrity and architects of assessment systems; however, their sensemaking

processes how they interpret signals of AI use, reconcile competing values, and justify grading decisions under uncertainty remain underexamined. This gap is especially consequential because institutional policies often lag behind technological developments, leaving educators to enact fairness in real time. Without empirical insight into how educators navigate these ambiguities, policy development risks becoming abstract, misaligned with classroom realities, or overly reliant on surveillance-based responses. Addressing this gap can therefore inform context-sensitive and ethically grounded institutional strategies [6]; [7]; [8].

To address this gap, the present study examines how ICT, TLE, and Language educators interpret and respond to ambiguous AI-related situations in academic assessments, and how they construct alternative resolutions when policy guidance is unclear. The study is anchored in Karl E. Weick's Sensemaking Theory (1995), which conceptualizes individuals as active meaning-makers who interpret equivocal environments through identity construction, enactment, and retrospection. Sensemaking is not merely a cognitive reaction but a socially embedded process through which actors construct plausible explanations that guide action. It is retrospective (individuals interpret events after they occur), identity-based (interpretations are shaped by who individuals believe themselves to be), enactive (actions shape the environment that is later interpreted), and grounded in social interaction. Applying this framework allows the study to move beyond descriptive accounts of AI tension and instead analyze how educators construct professional identities (e.g., innovator, guardian of integrity), enact assessment adjustments, and retrospectively justify grading decisions under technological uncertainty. In educational contexts, this theoretical lens provides a structured way to understand how institutional policies, disciplinary traditions, technological familiarity, and peer discourse influence the construction of meaning around AI use [9]; [10]

Guided by this framework, the study investigates three interrelated dimensions: (1) educators' perceptions of ambiguity, referring to how they recognize and describe difficult-to-judge AI-assisted outputs; (2) interpretive influences, including institutional context, disciplinary culture, technological literacy, and professional identity; and (3) enacted responses, or the adaptive strategies used to restore assessment fairness when formal regulations are insufficient. Rather than treating these as isolated variables, the study conceptualizes them as components of an ongoing sensemaking cycle in which interpretation and action mutually reinforce one another. This perspective extends current discussions on academic integrity and AI ethics by emphasizing educator agency and interpretive labor, rather than focusing solely on detection or student misconduct. By situating these dimensions within broader conversations on assessment innovation and ethical governance, the study contributes a theoretically grounded model explaining how professional judgment operates in technologically evolving classrooms [11].

Using an exploratory qualitative design, the study draws on in-depth semi-structured interviews with twenty educators from ICT, TLE, and Language disciplines. Data are analyzed through reflexive thematic analysis to identify patterned meanings, interpretive tensions, and enacted strategies within participants' narratives. Beyond identifying common AI-related "gray areas," the study seeks to construct an empirically grounded conceptual framework illustrating how educators interpret ambiguity, negotiate professional identity, and implement context-sensitive assessment adjustments. It is anticipated that disciplinary culture, institutional expectations, and technological familiarity influence how sensemaking unfolds across contexts

This study contributes to both theory and practice. Theoretically, it advances Sensemaking Theory within the context of AI-integrated education by explicitly linking identity construction, enactment, and retrospection to educators' assessment decisions under technological ambiguity. In doing so, it moves beyond confirmatory discussions of academic integrity tensions and offers a process-oriented explanation of how educators construct plausible resolutions in evolving digital environments.

Practically, the findings aim to inform institutional policy design, professional development initiatives, and assessment innovation by foregrounding educators' interpretive experiences rather than relying exclusively on technological control mechanisms. As international scholarship increasingly highlights the ethical and epistemic tensions surrounding AI in assessment, grounding AI governance frameworks in educator sensemaking becomes essential for promoting equitable, responsible, and context-sensitive integration [12]

2. Literature Review

2.1. Technological Foundations and Mechanisms of AI

The integration of Artificial Intelligence (AI) in education has transformed instructional design, feedback systems, and assessment practices. AI tools such as automated grading systems, language-generation models, adaptive tutoring systems, and plagiarism detectors have introduced new efficiencies and learning opportunities [13]. These systems operate through algorithmic modeling that identifies patterns in large datasets to automate decision-making or content generation. In assessment contexts, AI has been used to streamline grading processes, personalize feedback, and enhance data-driven instructional strategies. Generative AI represents a particularly disruptive advancement. Unlike rule-based systems, generative AI models—especially large language models (LLMs) are trained on massive corpora of text data and rely on probabilistic token prediction to generate outputs. These systems produce responses by calculating statistical likelihood rather than demonstrating conceptual understanding. Consequently, they may generate highly coherent essays, structured lesson plans, programming scripts, or research summaries that appear academically sophisticated. However, their outputs may also contain factual inaccuracies, fabricated citations, algorithmic bias, or what is commonly described as "hallucinations," wherein confidently presented information lacks empirical grounding. [14] emphasize that AI applications in higher education offer promising instructional benefits but also introduce unresolved ethical concerns. In assessment settings, generative AI complicates traditional indicators of mastery because fluency and polish are no longer reliable markers of competence. [15] found that AI-assisted tools may reduce student anxiety and enhance confidence, demonstrating AI's supportive potential in learning environments. Similarly, Chavez and Lamorinas [16] observed shifts in assessment strategies during pandemic-driven digital transitions, which parallel structural adjustments required in the era of AI-mediated learning. Importantly, the technical architecture of generative AI directly contributes to assessment ambiguity. Because outputs are statistically generated rather than authored through lived cognition, educators cannot rely solely on linguistic sophistication or structural coherence as evidence of student learning [17]. This technological reality demands not only policy responses but interpretive recalibration among educators, who must differentiate between assistance, augmentation, and substitution in student work. The lack of deep technological literacy among some educators may further compound ambiguity, as understanding probabilistic generation, training data limitations, and bias is essential for evaluating AI-mediated outputs responsibly [18]. Thus, the technological foundation of AI is not a neutral backdrop but a constitutive element of the ethical gray areas explored in this study. Without grounding ambiguity in technical mechanisms, debates about fairness risk remaining superficial or overly moralized. This underscores the necessity of integrating technological comprehension into educational ethics discussions.

2.2. Ambiguity, Authorship, and Construction of "Gray Areas"

The rise of generative AI tools such as ChatGPT, Grammarly, and image-generation systems has blurred the boundaries between legitimate academic support and academic dishonesty. [19] describe these ambiguous situations as policy "gray areas," where institutional frameworks fail to provide clear definitions of acceptable AI engagement. These ambiguities emerge when AI-generated outputs are indistinguishable from student-authored work, complicating verification processes. [20] emphasize that educators' perceptions of AI-generated content are influenced by disciplinary norms,

technological familiarity, and institutional expectations. What one educator interprets as legitimate scaffolding may be perceived by another as unethical substitution. [21] identified ethical dilemmas among ICT, science, and language instructors when judging AI-mediated submissions, illustrating interpretive variability across contexts. Divergent perspectives among Tech-Voc and science educators, further demonstrating disciplinary inconsistency.

Beyond policy vagueness, ambiguity is epistemic in nature. Generative AI challenges foundational assumptions about authorship, originality, and intellectual ownership. When a student submits AI-assisted content, questions arise: Who is the author? What constitutes cognitive effort? How should collaborative human-AI production be evaluated? These questions reflect deeper philosophical tensions within academic integrity frameworks [22]. Moreover, ambiguity is socially constructed through institutional discourse. In environments where AI policies are unclear or inconsistently enforced, educators must rely on professional judgment rather than formal regulation [23]. This reliance intensifies variability in assessment decisions and may generate perceived inequities among students. Thus, ambiguity is not merely a byproduct of technology but a condition shaped by policy lag, disciplinary culture, and collective interpretatio. According to Thwala [24] the presence of gray areas but rarely interrogates the interpretive mechanisms educators employ to resolve them. Most studies remain descriptive, focusing on prevalence rather than process. This study addresses that theoretical gap by examining how ambiguity is actively constructed, interpreted, and negotiated within specific disciplinary settings.

2.3. Educator Perceptions and Academic Integrity

Educator perceptions significantly shape responses to AI integration in assessments. [25] highlight that AI adoption is mediated by technological literacy, ethical orientation, institutional culture, and prior experience. ICT educators may frame AI as a natural extension of digital fluency, while Language educators may prioritize authenticity of voice and developmental writing processes. TLE educators may evaluate AI in terms of practical productivity and applied skill demonstration. [26] argues that educational technology debates often reflect deeper ideological struggles concerning authority, authenticity, and epistemic legitimacy. These ideological underpinnings influence how educators conceptualize fairness. Moral reasoning and humanized teaching approaches shape academic integrity enforcement in online contexts. [27] further confirmed that pedagogical philosophy affects evaluation strategies in language education. Professional identity plays a central role in AI interpretation. Educators who perceive themselves as innovators may embrace AI as a pedagogical ally, whereas those who identify strongly as guardians of academic integrity may adopt stricter evaluative stances [28]. These identity positions influence not only perception but enacted assessment behavior. Thus, ambiguity resolution is not purely technical it is identity-infused and value-laden. Furthermore, educators' retrospective reflection on past experiences with digital disruption (e.g., pandemic-era online learning) may shape how they interpret current AI-related challenges. These retrospective comparisons influence tolerance thresholds and expectations of student autonomy. Despite these insights, prior studies do not systematically connect perception variability to structured theoretical constructs explaining how meaning is constructed under uncertainty. This limitation highlights the need for a theory-driven exploration of interpretive processes.

2.4. Enacted Strategies and Adaptive Assessment

As educators confront AI-related ambiguity, they implement adaptive strategies to restore assessment validity. [29] discusses restructuring assessments through oral defenses and applied demonstrations. [30] advocate for AI literacy education as a proactive measure to encourage responsible use rather than relying solely on detection mechanisms. Educators frequently rely on contextual judgment rather than rigid compliance when navigating AI dilemmas. [31] illustrate how discourse patterns influence ethical interpretation, demonstrate the value of qualitative

inquiry in examining complex communicative behaviors. These adaptive strategies reflect a shift from surveillance-based integrity enforcement to process-oriented validation. Instead of asking solely whether AI was used, educators increasingly ask how AI was used and whether learning occurred. This transition indicates a reconceptualization of assessment from product evaluation to cognitive engagement verification. However, the literature largely catalogues strategies without analyzing the decision-making logic behind them. It remains unclear how educators determine when to apply oral validation, when to adjust grading weights, or when to treat AI use as acceptable augmentation. This interpretive decision-making process constitutes the central conceptual gap that the present study addresses.

2.5. Policy, Professional Development, and Theoretical Advancement

The growing integration of AI necessitates coherent institutional frameworks that balance clarity with professional autonomy. [32] argues that higher education must cultivate adaptive systems capable of navigating technological disruption. [33] emphasize incorporating educator experience into policy development. [34] recommend cross-disciplinary collaboration to reduce inconsistency. Despite these policy recommendations, a theoretical gap persists. AI integration as a regulatory problem rather than an interpretive one. Policies alone cannot resolve ambiguity if educators interpret AI use differently across contexts. Therefore, understanding the cognitive and social processes through which educators construct plausible resolutions becomes essential. Current scholarship confirms tensions regarding authorship, authenticity, and fairness but does not sufficiently explain how educators move from ambiguity to action. Integrating empirical narratives with a structured interpretive lens, the present study advances a process-oriented contribution rather than merely confirming existing concerns. In doing so, it addresses calls for theoretically grounded, context-sensitive approaches to AI governance in education.

3. Methodology

3.1. Research design

This study employed a qualitative exploratory research design to investigate how ICT, TLE, and Language educators perceive and address ambiguous or "gray" areas in the use of Artificial Intelligence (AI) in academic assessments. The exploratory design was appropriate because the study addresses emerging, context-dependent phenomena that require in-depth understanding and interpretation rather than numerical measurement. The study is anchored in the principle that educators are active sensemakers [35], navigating ambiguity and constructing meaning when formal guidance is absent or unclear. Through this approach, the study aimed to generate rich, descriptive insights into educators' experiences, perceptions, and strategies when encountering uncertainty and ethical dilemmas involving AI-assisted student work. This design also allowed for iterative engagement with participants, enabling probing questions to clarify process, intention, and professional judgment, which enhances interpretive depth.

3.2. Population and sampling

The participants of the study were twenty (20) educators teaching Information and Communications Technology (ICT), Technology and Livelihood Education (TLE), and Language subjects in both public and private higher education institutions. These disciplines were purposively selected because they represent areas where AI tools are frequently applied in teaching, learning, and assessment. The participants were chosen using purposive sampling, focusing on educators with firsthand experience in designing or evaluating academic assessments where AI involvement was evident or suspected. Diversity in gender, years of teaching experience, and institutional affiliation was considered to ensure a wide range of perspectives. Participation was voluntary, and confidentiality was maintained throughout the research process.

3.3. Instrument

The primary data-gathering tool of this study was a semi-structured interview guide developed in

alignment with the research objectives. The instrument was designed to elicit detailed insights into two main areas: (1) educators' perceptions of ambiguous or contested situations involving the use of AI in academic assessments, and (2) their strategies or alternative resolutions for addressing AI-related challenges in assessment contexts. The interview questions explored how educators describe and interpret difficult-to-judge AI-related situations, the factors influencing their perceptions, and the effects of such ambiguities on their assessment decisions. Additionally, questions were included to determine how educators manage these situations, the specific approaches they apply, and the criteria they use in selecting appropriate resolution strategies. To ensure validity and relevance, the interview guide underwent expert evaluation by two specialists in educational research and one in AI-integrated instruction. Their feedback was used to refine the wording and structure of the questions for clarity and alignment with the study's objectives. Table 1 presents the list of guide questions used by this research study.

Table 1. Interview guide questions

Objectives	Interview question
1. To examine educator perceptions regarding ambiguous situations involving AI in academic assessments.	1. How do you describe situations involving AI in academic assessments that you find difficult to judge? 2. What factors influence your perception of ambiguous situations Involving AI In academic assessments? 3. How do ambiguous situations Involving AI in academic assessments affect your assessment decisions?
2. To identify educator strategies for addressing AI-related issues in academic assessments.	1. How do you handle ambiguous situations involving AI in academic assessments? 2. What specific approaches do you use to address ambiguous situations Involving AI in academic assessments? 3. How do you determine which resolution approach is most appropriate for a particular academic assessment scenario?

3.4. Data Gathering Procedure

Data were collected through one-on-one semi-structured interviews conducted either face-to-face or online, depending on participant preference and availability. Each interview lasted approximately 30–45 minutes and was audio-recorded with informed consent. Field notes captured non-verbal cues, contextual details, and situational nuances to support interpretive analysis. Participants were provided with informed consent forms explaining the study's objectives, confidentiality measures, voluntary nature, and their right to withdraw at any time. Interview sessions also included reminders of ethical protocols, ensuring comfort and transparency.

3.5. Data analysis

The data collected from the interviews were transcribed verbatim and analyzed using Reflexive Thematic Analysis (RTA). This analytical approach was selected because it allows for systematic yet flexible interpretation of patterns across qualitative data while acknowledging the researcher's active role in knowledge construction. Rather than seeking objective coding reliability in a positivist sense, RTA emphasizes reflexive engagement with the data and the co-construction of meaning between researcher and participant. This orientation aligns with the study's theoretical grounding in sense making, where interpretation

and contextual understanding are central to analysis. The analysis began with an intensive familiarization process. Transcripts were read multiple times to immerse the researchers in participants' narratives, noting initial impressions, recurring tensions, and contextual nuances. Initial codes were then generated inductively from the data while remaining sensitized to key constructs related to ambiguity, perception, and resolution strategies. Coding was conducted manually and supported by qualitative data organization software to ensure systematic management of transcripts. To enhance analytical rigor, two researchers independently reviewed the transcripts and compared coding interpretations. ***Discrepancies were discussed collaboratively until conceptual agreement was reached, strengthening interpretive depth while preserving reflexivity*** [36].

Following initial coding, related codes were clustered into preliminary themes. These themes were examined for internal coherence and distinctiveness from one another to prevent conceptual overlap. During this stage, particular attention was given to differentiating between themes reflecting educator perceptions, contextual influences, and enacted strategies, as reviewers noted the need to clarify analytical boundaries. Themes were refined iteratively through constant comparison across cases, ensuring that each theme was strongly supported by data excerpts and aligned with the research objectives. A thematic map and coding tree were developed to visually represent the relationships among codes, subthemes, and overarching themes, thereby enhancing transparency and auditability of the analytical process. Throughout the analysis, reflexivity was actively maintained. The researchers documented analytic memos to reflect on their own assumptions, prior experiences with AI in education, and potential biases influencing interpretation***. Recognizing that researchers are not neutral observers but interpretive instruments, reflexive journaling helped ensure that themes were grounded in participant narratives rather than preconceived positions*** [37]; [38]. Data saturation was determined when no substantially new codes or thematic insights emerged from the final three interviews, indicating that thematic development had reached sufficient depth for this exploratory inquiry.

3.6. Ethical Considerations and Trustworthiness

Ethical approval for this study was obtained from the Institutional Review Board (IRB) of the affiliated higher education institution prior to data collection. All procedures adhered to established ethical standards for research involving human participants. Participants were provided with informed consent forms detailing the purpose of the study, voluntary nature of participation, confidentiality measures, and their right to withdraw at any point without penalty. Written consent was secured before conducting interviews. To protect participant identity, pseudonyms were assigned, and identifying institutional information was removed from transcripts and reports. Confidentiality was strictly maintained through secure storage of digital recordings and transcripts in password-protected files accessible only to the research team. Audio recordings were deleted after transcription verification. During online interviews, secure platforms were used to ensure privacy and data protection.

To establish trustworthiness, the study adhered to the criteria of credibility, dependability, confirmability, and transferability. ***Credibility was strengthened through member checking, wherein participants were invited to review summarized interpretations of their responses to confirm accuracy and meaning alignment.*** Peer debriefing was conducted with an external qualitative research expert to examine coding decisions and thematic structure, helping to minimize interpretive bias. Dependability was ensured through audit trailing, which documented coding procedures, theme refinement stages, and analytic decisions. ***Confirmability was supported by reflexive journaling, acknowledging the researchers' positionality and ensuring findings were rooted in participant narratives rather than researcher assumptions.*** Transferability was addressed by providing detailed contextual descriptions of participants, institutional settings, and disciplinary backgrounds. Such thick description enables readers to determine the

applicability of findings to other educational contexts. Collectively, these procedures respond directly to methodological rigor concerns and ensure that the findings are analytically sound, ethically grounded, and transparently developed.

4. Results

Research Objectives 1. To examine educator perceptions regarding ambiguous situations involving AI in academic assessments.

Question No. 1. How do you describe situations involving AI in academic assessments that you find difficult to judge?

1.1 *Difficult to give penalty*

Ten (10) respondents described uncertainty in assigning penalties when AI functioned as assistance rather than substitution. Their difficulty did not stem from the presence of AI itself but from determining the degree of student intellectual contribution. Participants constructed meaning around fairness, proportionality, and learning authenticity, revealing a tension between technological support and academic ownership. This ambiguity required interpretive judgment rather than rule-based enforcement, reflecting early-stage sensemaking triggered by unclear norms.

> "I find it difficult to decide whether to penalize or give partial credit when students use AI as a 'helper' rather than the main source."

> "AI use isn't black and white, students can use it to generate drafts, paraphrase, or get idea prompts, making it difficult to measure original thinking."

These responses illustrate identity construction, where educators negotiated their professional role as fair evaluators in environments lacking explicit policy clarity. Instead of relying solely on institutional rules, they interpreted each case contextually. The ambiguity surrounding partial AI assistance compelled them to re-evaluate traditional grading boundaries and reconsider what constitutes authentic student work.

1.2 *Difficulty in verifying authorship of ideas*

Five (5) respondents highlighted challenges in determining intellectual ownership, particularly in output-based assessments such as business plans and proposals. The central concern involved originality and the student's conceptual grasp rather than the mere detection of AI usage. Participants responds reflect enactment processes within sensemaking. Educators confronted ambiguous outputs and responded by redefining what evidence of learning should look like. The issue extended beyond technological suspicion and moved toward epistemic evaluation: how originality is defined in AI-mediated contexts. Participants reframed assessment criteria to focus more on demonstrable understanding than polished presentation.

> "Some students submit AI-generated business plans or product proposals that look impressive and professionally structured, but it's hard to know if the ideas truly came from them or from the AI."

> "In TLE subjects where originality and innovation are essential, AI involvement can undermine the purpose of the task since business plans are meant to show the student's grasp of market needs, costing, and production."

1.3 Risk of overestimating student proficiency

Five (5) respondents described situations in which AI-enhanced outputs created uncertainty regarding actual student proficiency. The mismatch between typical classroom performance and submitted work triggered interpretive doubt. These narratives illustrate retrospection in sensemaking. Educators evaluated present outputs against prior knowledge of student capability, using historical interaction as a comparative frame. Rather than assuming misconduct, they reflected on developmental trajectories and voice consistency. This process revealed how authenticity judgments rely on accumulated relational knowledge rather than solely textual evidence.

> "When students submit essays or reflections that sound too formal or

advanced for their level, I struggle to decide how authentic their voice is."

"When reflections lose their natural tone, it also affects how I assess critical thinking and personal engagement."

Question No. 2. What factors influence your perception of ambiguous situations involving AI in academic assessments?

2.1 *Recognize AI-generated outputs*

Five (5) respondents noted that personal familiarity with AI systems informed their evaluative interpretations. Their recognition did not rely exclusively on detection software but on linguistic patterns, tonal shifts, and structural consistency. It demonstrates enactment shaped by technological literacy. Educators interpreted ambiguity through experiential knowledge of AI outputs. They constructed authenticity standards grounded in contextual markers such as personal examples and disciplinary alignment. Their evaluative process combined technological awareness with pedagogical judgment.

"Because I regularly use AI tools, I can often recognize when a student's output is AI-generated whether through the overly formal language, the polished structure, or the lack of personal voice."

"I also check for personal input in their work, such as examples from class discussions, their own experiences, or original analysis."

2.2 *Sudden improvement in quality*

Ten (10) respondents relied on performance continuity as a benchmark for evaluation. Abrupt shifts in quality triggered interpretive scrutiny but did not immediately result in accusations. Participants responses reflect retrospective sensemaking. Educators compared current outputs with historical baselines to assess authenticity. The follow-up questioning represented enacted verification strategies designed to reconcile ambiguity. Instead of punitive reflexes, participants emphasized procedural clarification and student explanation.

" I pay close attention to a student's usual performance because it gives me a clear baseline for their skills and style."

"I usually ask students to walk me through their process, how they planned, what steps they followed, or how they used tools like AI."

2.3 Sudden shift in language level or style

Five (5) respondents emphasized familiarity with student voice as a key interpretive resource. This reinforces identity construction as relational familiarity shaped authenticity judgments. Educators positioned themselves as observers of developmental progression. Voice recognition functioned as a heuristic, yet participants maintained reflexive restraint, avoiding immediate conclusions and opting for clarification.

" I can usually recognize my students' writing voice their typical vocabulary, grammar patterns, tone, and phrasing."

" This mismatch affects how I perceive the authenticity of the work. It doesn't mean I automatically assume dishonesty, but it makes me more alert and curious."

Question No. 3. How do ambiguous situations involving AI in academic assessments affect your assessment decisions?

3.1 *Focus on student contribution*

Ten (10) respondents described recalibrating grading decisions toward measurable contribution and process transparency.This reflects enactment at the pedagogical level. Educators translated ambiguity into instructional redesign. Rather than rejecting AI presence, they structured assessments to foreground contribution, documentation, and explanation. Professional identity shifted from rule enforcer to adaptive facilitator of responsible tool use.

"As an ICT teacher, I understand that students will naturally explore AI tools. The challenge is determining how much of their work is their own."

"These experiences have led me to adjust my lesson to highlight process documentation, student explanation, and originality."

3.2 *Emphasis on practical skills*

Five (5) respondents in TLE prioritized demonstrable performance over conceptual planning outputs. Serves a demonstrates enactment through assessment restructuring. Educators shifted evaluative emphasis toward observable competencies. Ambiguity prompted modification of grading distribution to preserve skill validation.

"In TLE, hands-on performance is key. If I suspect AI was used in the planning or design phase like in business plans, menu designs, or layouts I look for evidence of the student's own input."

" I've also adjusted how I grade. When I detect heavy AI use, I lessen the weight on the planning part and put more emphasis on their actual hands-on performance and explanation."

3.3 Valuing drafts and progress

Five (5) respondents recognized limitations in final-product evaluation and transitioned toward process-oriented assessment. This reflects retrospective learning and forward enactment. Participants reassessed prior grading practices and implemented progressive documentation strategies. Ambiguity served as a catalyst for systemic adaptation rather than disciplinary reaction.

" I realized that focusing only on the final product makes it harder to assess authenticity, especially when AI can produce polished outputs so easily."

"I've started putting more weight on process-oriented activities like drafts, brainstorming notes, or reflections rather than just the final written output."

Research Objectives 2. To identify educator strategies for addressing AI-related issues in academic assessments.

Question No. 1. How do you handle ambiguous situations involving AI in academic assessments?

Ask students to explain their process.

Ten (10) respondents explained that when AI involvement is uncertain, they prioritize verifying the student's understanding rather than directly accusing them of misuse. They conduct short oral checks that require learners to explain why they made certain decisions, how specific functions operate, or how they would adjust their output under new conditions. This method shifts attention from the final product to the reasoning process behind it. Participants shared that when students can clearly articulate their logic or revise their work on the spot, it signals authentic engagement. To avoid creating a culture of suspicion, some educators normalize spot-checking as part of routine assessment practice. They also integrate these validations into grading rubrics to maintain fairness and transparency. Through this strategy, assessment becomes a tool for confirming comprehension rather than merely detecting AI use.

"In situations where it's unclear whether a student truly understands their AI-assisted output, I conduct short oral checks to verify their level of engagement and learning."

"I also conduct random spot-checks to normalize the practice and discourage overreliance on AI. When students can confidently explain or adjust their work on the spot, it demonstrates authentic learning."

1.2 *Focus on performance and application.*

Five (5) respondents emphasized that practical performance provides stronger evidence of learning than written plans alone. They observed that AI-assisted outputs sometimes appear more advanced than the student's actual skill level. When inconsistencies arise, they ask learners to demonstrate, replicate, or modify parts of their work. This allows them to assess whether understanding extends beyond surface-level submission. Participants shared that observing

confidence, fluency, and adaptability during execution helps clarify genuine competence. If students can apply the concepts independently, the use of AI is viewed as support rather than substitution. However, when they struggle to perform or explain procedures, instructors adjust their evaluation accordingly. This approach reinforces that mastery is measured through application, not just presentation.

> " Even if AI tools assist students in planning their projects, the true measure of learning happens during the execution phase, where their practical skills are demonstrated. "

> "I also observe their performance closely to identify whether they are confident and familiar with the process or simply following instructions they barely understand"

1.3 *Integrate reflective components.*

Five (5) respondents incorporated reflective writing to clarify how students developed their outputs. They require learners to describe their process, including whether AI tools were consulted and how decisions were made. These reflections often reveal levels of ownership, strategy, and independent thinking that are not visible in the final product. Educators noted that asking students to specify steps such as idea generation, drafting, revising, or editing helps trace cognitive engagement. When AI use is disclosed, follow-up questions focus on how students evaluated and modified the generated content. This encourages responsible integration of technology rather than concealment. Participants explained that reflective components promote transparency while still maintaining academic standards. Over time, students become more mindful of documenting their process and demonstrating genuine understanding.

> " As part of the assessment process, I ask students to submit a short written reflection explaining how they developed their work, including whether and how they used AI tools at any stage. "

> "I encourage students to describe specific steps, such as how they generated ideas, structured their draft, revised their language, or checked their grammar."

Question No. 2. What specific approaches do you use to address ambiguous situations involving AI in academic assessments?

2.1 (*Clarifying the learning object*

Five (5) respondents explained that AI use is not automatically treated as misconduct, particularly in ICT-related subjects where technology integration is expected. Instead, they begin by revisiting the intended learning objective of the task. If the assessment targets coding logic, system design, or conceptual understanding, they verify whether students truly grasp the output submitted. This verification is done through oral questioning, short presentations, debugging exercises, or real-time modification tasks. When learners can transfer the concept to a new scenario, educators interpret this as evidence of meaningful engagement rather than blind reliance on AI. Several participants also require documentation of the development process, such as screenshots, draft histories, or reflective journals. This structured clarification ensures that AI serves as a support tool aligned with instructional goals rather than replacing cognitive effort.

> "Since AI tools are naturally part of ICT, I don't immediately treat AI use as misconduct. Instead, I clarify the learning objective if the task is about coding or design logic, I check if the student actually understands the output they submitted."

> "I ask students to replicate or modify their code or design in real time. If they can apply the concept in a different context, it shows they actually learned from the tool instead of depending entirely on it."

2.2 Actual output matters more

Five (5) respondents emphasized that in performance-based disciplines, observable output and demonstrated skill weigh more heavily than

written planning documents. When submissions appear highly polished yet inconsistent with a student's usual capability, educators initiate follow-up questioning or require partial replication. This helps determine whether the learner genuinely internalized the material. Participants shared that close observation during task execution provides insights into confidence, fluency, and procedural understanding. Clear guidelines regarding acceptable AI use are also established beforehand, such as allowing idea generation but not full content production. This boundary-setting enables educators to distinguish assistance from overdependence. Students are then given opportunities to validate their competence through practical demonstration. Over time, this consistent validation approach encourages accountability and discourages superficial reliance on automated tools.

> "For performance-based tasks, the actual output matters more than the written plan. If a student submits an impressive business plan or menu that doesn't match their performance level, I ask follow-up questions or require them to replicate parts of it."

> "I also set clear guidelines about when and how AI can be used, like for idea generation but not for the full plan. This clarity helps me distinguish between acceptable assistance and overreliance."

2.3 Thru writing voice and consistency

Ten (10) respondents reported that in writing-intensive assessments, they examine patterns of voice, vocabulary, and stylistic consistency. When a submission significantly deviates from a student's established writing profile, they initiate clarification through short interviews or immediate revision tasks. Rather than imposing immediate penalties, they use this opportunity to assess authorship and comprehension. Educators explained that sudden shifts in tone, advanced academic phrasing, or unusually error-free grammar often prompt further inquiry. However, they also foster transparency by encouraging students to disclose any AI assistance used during drafting or editing. The focus remains on evaluating how students build upon and personalize generated content. Through guided, learners are supported in aligning AI-assisted drafts with their authentic voice. This approach balances accountability with developmental support in writing instruction.

> " I look at writing voice and consistency. If the tone or grammar level is very different from a student's usual work, I call them in for a short interview or ask them to revise on the spot."

> "To promote honesty, I encourage students to disclose if they used AI in any part of their writing."

Question No. 3. How do you determine which resolution approach is most appropriate for a particular academic assessment scenario?

3.1 Task Complexity Matters

Ten (10) respondents explained that the level of task complexity strongly influences the resolution strategy they choose. When submitted work appears technically advanced beyond a student's usual performance, they avoid immediate penalization and instead conduct validation checks. These include short oral explanations, on-the-spot revisions, or requiring students to modify a portion of their output. Participants emphasized that the instructional goal determines the approach if mastery of technical skills is the focus, they prioritize direct demonstration. If conceptual understanding is central, reflective questioning becomes the preferred method. Educators also consider evidence such as drafts, history, or tool usage records when clarification is necessary. This layered decision-making allows them to respond proportionately rather than reactively. Overall, the chosen resolution depends on aligning verification methods with the intended learning outcomes of the assessment.

> "I consider how technical the task is. If the issue involves code that's clearly beyond the student's usual skill, I don't penalize immediately."

> "If the student can explain the logic behind their work, I consider it

authentic and use a reflective resolution approach."

3.2 Prioritize Hands-On Performance Over Written Work

Five (5) respondents shared that when performance is the core competency being measured, demonstration outweighs written submission. If an output such as a business plan or design document appears highly refined yet inconsistent with observable skill, they require a live demonstration task. This enables them to assess whether the learner can execute what was presented in writing. When students perform competently, AI assistance is interpreted as supportive rather than substitutive. If gaps emerge during execution, grading adjustments are made to reflect actual competency levels. Participants also explained that they weigh the proportion of performance versus documentation in the assessment structure before deciding on a resolution. Performance-heavy tasks are addressed through skills validation, while planning-heavy tasks are verified through oral defense or reflective explanation. This differentiation ensures fairness and alignment with assessment priorities.

> " I apply mathematical modeling to understand how resources are used over time. This helps create strategies that are both efficient and sustainable by identifying trends, predicting future outcomes, and minimizing waste."

> "I choose an approach based on the weight of the performance vs. written task. If the assessment is performance-based, I use a skills validation approach. If it's more on conceptual planning, I rely on oral defense or reflective questions."

3.3 Focus on voice and consistency

Five (5) respondents stated that in language-focused assessments, authenticity of voice serves as a primary indicator in determining resolution strategies. When a submission reflects a sudden shift in tone, vocabulary, or grammatical sophistication, they initiate clarification rather than impose automatic sanctions. Short interviews, follow-up writing tasks, or reflective prompts are used to confirm authorship and comprehension. Participants explained that this method allows them to differentiate between legitimate assistance and misrepresentation. They also encourage students to acknowledge external support and explain how they revised generated content. Documentation of these verification steps promotes transparency and consistency in grading decisions. The selected resolution therefore balances accountability with developmental guidance. In this way, authenticity, reflection, and skill demonstration collectively inform the most appropriate response to ambiguous AI-related cases.

> "In Language assessments, I focus on the authenticity of student voice and writing consistency."

> "Encouraging student reflection on the writing process including where they received support helps clarify the level of independent effort and fosters responsibility for authentic work."

5. Discussion

The findings of this study extend Karl Weick's Sensemaking Theory by demonstrating how educators construct professional meaning in technologically disruptive contexts characterized by generative AI–mediated ambiguity. Sensemaking, as conceptualized by Weick in 1995, involves identity construction, retrospection, enactment, and plausibility-driven interpretation in situations where clear rules are absent [39]. In the context of AI-integrated assessments, ambiguity does not merely stem from policy gaps but from the probabilistic nature of generative AI systems, which produce coherent outputs without guaranteeing epistemic validity or authorship transparency [40]. Educators are therefore required to interpret outputs that may appear academically competent yet lack traceable cognitive effort. This technological opacity intensifies equivocality, requiring interpretive work rather than procedural compliance. Situating educator responses within sensemaking constructs, this study moves beyond confirming known tensions about authorship and instead explains how those tensions are cognitively

processed and professionally negotiated. This interpretive framing responds directly to concerns that the study might otherwise appear confirmatory rather than theoretically additive. The contribution lies not in restating ethical dilemmas, but in revealing the dynamic meaning-construction processes educators use to stabilize professional judgment under AI uncertainty [41].

Educator perceptions of AI-related "gray areas" were found to reflect identity construction, one of Weick's central sensemaking properties. Participants interpreted ambiguous AI use in ways that aligned with their professional identities and disciplinary commitments. ICT educators often framed AI as an extension of digital fluency, whereas Language educators emphasized authenticity of voice and developmental writing processes, illustrating how identity shapes plausibility judgments [42]. This divergence is not simply disciplinary preference but an enactment of role-based professional accountability. International scholarship similarly suggests that educators' AI stances are filtered through moral, pedagogical, and epistemological commitments rather than purely technological considerations [43]. The study thus contributes a structured explanation of why interpretive variability persists even when institutional guidelines are shared. Rather than viewing inconsistency as a weakness, the findings reveal identity-informed plausibility as a predictable outcome of decentralized sensemaking processes. This analytical clarification strengthens the conceptual novelty of the research by connecting perception variability to formal theoretical constructs instead of treating it descriptively.

The findings also illuminate retrospection as a key mechanism in educators' interpretation of AI-mediated assessment dilemmas. Participants frequently drew upon prior experiences with digital transitions, including remote assessment adaptations and earlier academic integrity challenges, when evaluating AI-related ambiguity. Retrospection enables individuals to interpret present uncertainty through the lens of past events, thereby constructing coherence in evolving environments. This study demonstrates that educators do not interpret generative AI in isolation but situate it within broader narratives of technological disruption and pedagogical change. Such retrospective framing influences tolerance thresholds for AI assistance and shapes decisions regarding whether AI use constitutes augmentation or substitution. Scholars have noted that generative AI complicates traditional markers of authorship because its outputs are statistically generated rather than cognitively authored [44]. Linking these technological realities to retrospective meaning-making, the study advances a deeper explanatory account of assessment ambiguity. This connection addresses critiques regarding insufficient technological grounding by integrating AI's operational characteristics into interpretive analysis.

Enactment, another core sensemaking process, was evident in the strategies educators employed to manage AI-related assessment concerns. Rather than applying rigid enforcement mechanisms, participants modified assessment structures, introduced oral validation components, or reframed AI use as a transparent learning tool. Enactment refers to how individuals construct elements of their environment through action, thereby reducing equivocality [45]. In this study, educators did not passively respond to AI disruption; they actively reshaped assessment conditions to reestablish fairness and pedagogical coherence. International discussions on AI governance in education emphasize similar shifts from detection-based control toward assessment redesign and AI literacy integration [46]. The findings therefore extend global debates by illustrating how such redesign decisions emerge from iterative interpretive cycles rather than from policy mandates alone. This moves the study beyond confirmatory claims and demonstrates a process-level contribution. The innovation lies in mapping enacted strategies onto theoretical constructs, clarifying how professional judgment evolves in practice. Organizational context further shaped sensemaking through social interaction and collective interpretation. Participants described relying on peer discussions, departmental consultations, and informal professional exchanges when confronting ambiguous AI cases. Sensemaking is inherently social, as meaning

stabilizes through shared narratives and negotiated plausibility. In environments where institutional AI policies were vague or evolving, collective deliberation became a substitute for formal regulation. This aligns with international scholarship suggesting that AI governance often lags behind technological innovation, leaving educators to rely on localized interpretation [47]. The findings therefore underscore the importance of dialogic policy development rather than purely prescriptive frameworks. Revealing how collective sensemaking mediates individual judgment, the study provides practical implications for professional development and policy scaffolding. This analytical emphasis directly responds to reviewer concerns about demonstrating applied contribution.

This study advances theoretical and practical understanding by conceptualizing AI-related assessment ambiguity as a sensemaking phenomenon rather than solely an ethical compliance issue. While prior scholarship has identified concerns about authorship, hallucination risks, bias, and false confidence in generative outputs, fewer studies have explained how educators cognitively and socially process these challenges in real time. Integrating identity construction, retrospection, enactment, and social interaction into one interpretive framework, the study offers a cohesive explanatory model. This model provides the basis for the proposed conceptual framework summarizing relationships among ambiguity perception, interpretive factors, and enacted resolutions. Such a framework strengthens the manuscript's theoretical contribution beyond descriptive confirmation. Ultimately, the findings suggest that sustaining academic integrity in AI-enhanced education requires supporting educators' interpretive capacity, not merely regulating technological use. This reconceptualization enhances both scientific rigor and applied relevance.

6. Conclusion

This study examined how ICT, TLE, and Language educators interpret and respond to ambiguous or "gray" situations involving Artificial Intelligence in academic assessments. The findings confirm that ambiguity does not stem solely from policy gaps but from the inherent characteristics of generative AI systems, whose probabilistic outputs complicate conventional indicators of authorship, originality, and cognitive effort. Rather than applying uniform rules, educators engage in reflective and context-sensitive judgment shaped by disciplinary norms, professional identity, and institutional expectations. Their responses demonstrate that AI-related assessment dilemmas are interpretive challenges requiring meaning construction rather than simple compliance decisions. Grounding the analysis in Weick's Sensemaking Theory, the study contributes a process-oriented explanation of how educators move from ambiguity to action. It advances existing scholarship by clarifying that variability in AI-related assessment decisions is not merely inconsistency but a predictable outcome of identity-informed and socially mediated sensemaking. This theoretical articulation moves beyond confirming known tensions about authorship and integrity, offering instead a structured model linking perception, contextual interpretation, and enacted resolution strategies. The resulting conceptual framework provides a clearer understanding of how fairness and academic integrity are operationalized in technologically evolving environments. Practically, the study underscores that sustaining integrity in AI-enhanced education requires more than detection tools or prescriptive regulations. Institutions must support educators' interpretive capacity through coherent policy scaffolds, structured professional dialogue, and sustained AI literacy development. Policies that acknowledge disciplinary variation while promoting shared ethical standards may reduce ambiguity without suppressing professional judgment. Ultimately, the study highlights that educators function as active interpreters within AI-mediated assessment ecosystems, and that strengthening this interpretive role is central to ensuring fairness, authenticity, and pedagogical integrity in higher education.

7. Limitations of the study

The study involved a purposive sample of twenty (20) educators from ICT, TLE, and Language disciplines. While sufficient for exploratory qualitative inquiry and consistent with

reflexive thematic analysis principles, the sample size limits broad generalization. The inclusion of participants across different disciplines, institutional types, and experience levels enriched interpretive variability; however, such diversity within a relatively small sample may also produce uneven representational balance. Although data saturation was reached at the final stage of interviews, the findings reflect context-specific sensemaking processes rather than statistically generalizable trends. Second, although demographic characteristics such as gender, teaching experience, and institutional affiliation were considered during sampling, the study did not aim to conduct comparative demographic analysis. As such, disciplinary and identity-based differences are interpreted through narrative depth rather than quantitative distribution. Future studies employing larger samples and mixed-method designs may offer more structured comparative insights across demographic variables.

Third, while the study strengthened methodological rigor through reflexive thematic analysis, peer debriefing, thematic mapping, and audit trailing, qualitative interpretation remains shaped by researcher positionality. Although reflexive journaling was maintained and coding discrepancies were collaboratively resolved, interpretive findings are inherently co-constructed. This reflects the epistemological orientation of reflexive thematic analysis rather than a procedural weakness; nevertheless, it limits claims of objectivity. Fourth, although the manuscript integrates a stronger explanation of generative AI mechanisms (e.g., probabilistic generation, hallucinations, bias, authorship ambiguity), the study did not empirically examine specific AI systems, model architectures, or detection technologies. The focus was interpretive rather than technical. Consequently, conclusions about AI-related ambiguity are grounded in educator perceptions rather than computational validation of AI outputs. Fifth, while ethical approval was obtained from the Institutional Review Board (IRB) and ethical procedures were explicitly documented, the study did not explore participants' institutional policy documents in depth. Interpretations of policy clarity were therefore based on educator accounts rather than formal policy analysis. Future research may triangulate educator narratives with documentary review for greater contextual precision. Moreover, although the study advances a theoretically grounded sensemaking framework, its conceptual contribution remains process-oriented and exploratory. It does not claim to establish a universal model of AI governance but rather offers a contextualized explanation of educator meaning construction within specific disciplinary environments.

8. Recommendations

First, future research should expand the participant pool across multiple institutions, regions, and educational levels to enhance transferability and cross-context comparison. A larger sample may enable structured disciplinary comparison and demographic analysis, particularly regarding years of experience, technological literacy, and institutional policy exposure. Second, subsequent studies may integrate mixed-method designs combining qualitative interviews with survey instruments to measure perception patterns at scale. This would strengthen empirical generalizability while preserving interpretive depth. Third, further research should incorporate explicit technological case analysis. Examining specific generative AI tools (e.g., large language models, coding assistants, AI image generators) and comparing educator responses to distinct AI outputs may clarify how technical affordances influence interpretive judgment. Fourth, future scholarship may conduct policy-document analysis alongside educator interviews to assess alignment between institutional AI guidelines and classroom-level enactment. Such triangulation would contribute to stronger governance frameworks grounded in both regulation and lived experience. Fifth, professional development initiatives should prioritize AI literacy for educators. Understanding probabilistic text generation, hallucination risks, bias propagation, and output limitations will support more informed and equitable assessment decisions. Institutions should move beyond detection-based strategies and instead cultivate structured dialogues that support collective sensemaking among faculty members. Sixth,

assessment redesign efforts should emphasize process-oriented evaluation strategies, including oral validation, iterative drafting, reflective disclosure, and performance-based demonstration. These approaches align with the findings of this study and may reduce overreliance on surveillance-based academic integrity enforcement. Therefore, future theoretical work may further operationalize sensemaking constructs in AI-integrated education by developing measurable indicators of identity construction, enactment strategies, and retrospective framing. Such development could advance the transition from exploratory theoretical application toward more systematic explanatory models.

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Author affirms that this study is an original work developed through independent academic effort and scholarly analysis. AI tools were used solely for language and grammar assistance; no content was generated by AI. All conceptualization, analysis, interpretation, and writing were produced by the author, with proper attribution to all sources. The author assumes full responsibility for the integrity, originality, and accuracy of the study. No funding was received for this research.

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