

# AIMIL-Based Human-AI Judgement for Inclusive Academic Research

Saidatul Akmar Ismail<sup>1</sup>, Wan Satirah Wan Md Saman<sup>1</sup>, Md Hafizi Ahsan<sup>2</sup>,  
Nurul Huda Md Yatim<sup>3</sup>

<sup>1</sup>Faculty of Information Science, Universiti Teknologi MARA, Selangor Branch, Malaysia

<sup>2</sup>Labuan Faculty of International Finance, Universiti Malaysia Sabah, Labuan International Campus, Malaysia

<sup>3</sup>Faculty of Information Science, Universiti Teknologi MARA, Johor Branch, Malaysia

\*Corresponding author: Saidatul Akmar Ismail (saidatulakmar@uitm.edu.my)

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## ABSTRACT:

Generative artificial intelligence (GenAI) is increasingly embedded in academic research and can improve access for learners with disabilities through conversational search, simplification, translation, multimodal interaction, and assistive writing support. Yet AI-generated outputs may fabricate citations, obscure provenance, compress uncertainty, and encourage over-reliance on fluent but unsupported claims. This conceptual paper develops AI-Mediated Information Literacy (AIMIL) as a theory of responsible human judgement in AI-mediated information environments and proposes the AIMIL Inclusive Human-AI Information Judgement Model (AIMIL-IHIJ). A targeted conceptual review synthesises recent 2022–2026 literature on information literacy, AI literacy, critical AI literacy, Universal Design for Learning (UDL), GenAI reliability, academic-library instruction and inclusive education, supplemented by a small number of foundational sources. AIMIL is distinguished from adjacent frameworks by its explicit focus on claim-level provenance, recursive verification and accountable knowledge construction. The model comprises six capabilities: Frame, Engage, Triangulate, Trace, Verify, and Construct. These operate under three safeguards: accessibility and learner agency, human epistemic oversight and ethical responsibility. It introduces epistemic accessibility as the capacity not only to reach and understand information but also to trace, evaluate, and defend knowledge claims. Eight propositions are advanced for empirical testing, and an applied academic-library training architecture is outlined. A pseudonymised practice vignette from the researcher's own unpublished internal institutional report is used only to demonstrate the current normalisation of AI-enabled, industry-connected learning environments. The paper argues that inclusive AI use should expand participation without displacing the learner's responsibility for evidence, provenance and scholarly judgement.

**Keywords:** AI-mediated information literacy (AIMIL), human-AI judgement, students with disabilities, academic libraries, responsible AI

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## 1. Introduction

Generative AI has moved from an experimental technology to an everyday component of higher education. Students and researchers use conversational systems to generate keywords, clarify concepts, summarise texts, translate technical language, compare perspectives, and draft explanations. This shift changes the architecture of information seeking because the learner may encounter a machine-produced synthesis before reaching the scholarly record itself (Crompton & Burke, 2023; Kasneci et al., 2023; Xia et al., 2024). For learners with disabilities, these systems may also reduce barriers through speech-based interaction, re-expression, text simplification, and multimodal assistance. Recent empirical work shows that students with disabilities are already using GenAI for academic tasks while expressing concern about accuracy, integrity, and the adequacy of institutional guidance (Zhao et al., 2025; Waterfield et al., 2026).

Accessibility, however, is not equivalent to reliability. Large language models can fabricate references, misattribute claims, omit methodological qualifications, and produce persuasive but unsupported prose (Gravel et al., 2023; McGowan et al., 2023; Walters & Wilder, 2023). These limitations matter in academic research because a credible claim depends on traceable evidence, not on stylistic fluency. The educational problem is therefore not simply whether students can operate AI tools, but whether they can retain intellectual and ethical authority over information when AI mediates discovery, explanation, and synthesis.

Academic libraries are well positioned to respond. Their established responsibilities for searching information, source evaluation, citation, scholarly communication and information ethics now require an extension from information retrieval to human-AI information judgement. Recent library scholarship similarly argues for GenAI competencies grounded in the ACRL Framework and for a more proactive library role in AI-rich knowledge environments (Khailova et al., 2026; Kim, 2025). This paper proposes AI-Mediated Information Literacy (AIMIL) as that extension. AIMIL treats information literacy as a mediated, recursive, and accountable practice in which the human researcher remains responsible for what enters the scholarly record.

The paper has four aims: to explain how GenAI changes information judgement; to distinguish AIMIL from ACRL Information Literacy, AI literacy, critical AI literacy, and UDL; to propose the AIMIL-IHJ model and its theoretical propositions; and to show how academic-library training can support inclusive, evidence-grounded AI use.

## 2. Methodology

This conceptual paper uses a targeted review for theory construction rather than a systematic review or

meta-analysis. Priority was given to peer-reviewed literature published from 2022 to 2026 on GenAI in higher education, AI literacy, critical AI literacy, information literacy, academic libraries, inclusive education, students with disabilities, UDL, provenance, and citation reliability. Foundational works were retained where necessary for conceptual genealogy, including the ACRL Framework, early AI-literacy models, and established educational-technology theory (Association of College and Research Libraries, 2016; Long & Magerko, 2020; Ng et al., 2021). International policy sources were included where they directly informed responsible and inclusive AI practice (European Commission, 2022; UNESCO, 2023, 2024).

The synthesis proceeded in three stages. First, the primary object and limits of each adjacent framework were identified. Second, unresolved gaps at their intersections were examined, particularly the absence of a provenance-centred model for deciding whether AI-mediated information deserves to enter academic work. Third, integrative constructs and eight propositions were formulated around human epistemic responsibility, recursive verification, learner agency, and epistemic accessibility. An IJSE-specific overlap check was also used to avoid duplicating the journal's recent work on adaptive systems, assistive technologies, explainability, privacy, and general AI applications in special education (Buch et al., 2026; Kumar et al., 2026; Soni et al., 2026).

To strengthen ecological relevance without treating institutional observations as empirical data, the paper also draws on the researcher's own unpublished internal report submitted to Institution A in 2026 (Author, 2026). The report is used only as a practice-grounding vignette. Institutional names, geographic setting, exact timing, industry partners, programme names, and other potentially identifying combinations are withheld or generalised. No participants were recruited and no primary personal data were collected; therefore formal human-subject ethics approval was not required.

## 3. Results

### 3.1 Why AIMIL is Needed

GenAI inserts a generative intermediary between the researcher and the scholarly record. This creates three recurring risks. First, provenance may be obscured: an answer can sound scholarly without exposing a stable evidence chain. Second, uncertainty can be compressed: contested or population-specific findings may be presented as a single confident narrative. Third, reduced search friction may encourage epistemic dependency, where the researcher delegates not only access but also evaluative judgement to the system. Prompt engineering alone cannot solve these problems because a better prompt does not guarantee valid evidence.

AIMIL therefore distinguishes transformation tasks from evidential tasks. Transformation tasks operate on material already supplied or verified by the learner, such as reformatting notes or simplifying a passage. Evidential tasks introduce or evaluate claims about the world, such as recommending sources, interpreting findings, or deciding that evidence supports a conclusion. Verification intensity should increase with the epistemic consequence of the AI contribution. Provenance must also be understood semantically: a reference may be real but still fail to support the specific claim attributed to it.

3.2 AIMIL and Adjacent Frameworks

ACRL Information Literacy remains foundational because it emphasises authority, inquiry, creation, scholarly conversation, and strategic searching.

AIMIL extends it by making AI-mediated provenance and recursive verification explicit. AI literacy concerns understanding AI concepts, capabilities, limitations, evaluation, and ethical use (Laupichler et al., 2022; Lintner, 2024; Pinski & Benlian, 2024). AIMIL accepts these competencies but asks a narrower scholarly question: what procedures allow a human researcher to justify an AI-assisted claim against traceable evidence? Critical AI literacy adds interrogation of power, bias, data practices, and social inequality (Veldhuis et al., 2025); AIMIL connects these concerns to claim-level evidence checking. UDL contributes accessibility, flexibility, and learner agency through multiple means of engagement, representation and action (CAST, 2024), while AIMIL specifies how information claims should be judged within those inclusive environments.

Table 1. AIMIL compared with adjacent frameworks

| Framework                 | Primary focus                                     | Key strength                                                     | AIMIL extension                                                |
|---------------------------|---------------------------------------------------|------------------------------------------------------------------|----------------------------------------------------------------|
| ACRL Information Literacy | Participation in scholarly information ecosystems | Authority, inquiry, search, creation, value                      | Adds AI-mediated provenance and recursive verification         |
| AI literacy               | Understanding and using AI                        | Capabilities, limitations, evaluation, ethics                    | Centres evidence warrant and source authentication             |
| Critical AI literacy      | AI as sociotechnical system                       | Power, bias, justice, reflexivity                                | Connects critique to claim-evidence verification               |
| UDL                       | Inclusive learning design                         | Multiple means, access, learner agency                           | Provides accessibility architecture for evidence judgement     |
| AIMIL                     | Human judgement in AI-mediated research           | Framing, triangulation, provenance, verification, accountability | Integrates the four foundations around epistemic accessibility |

3.3 Epistemic Accessibility and the AIMIL-IHIJ Model

For inclusive higher education, technical accessibility is necessary but insufficient. A learner may be able to obtain an AI-generated answer yet remain unable to determine where it came from or whether it deserves trust. This paper therefore defines epistemic accessibility as the capacity to access information, understand its meaning, identify its provenance, evaluate its credibility, recognise uncertainty, compare alternatives, and make an independently defensible judgement. This avoids both AI prohibition, which can remove useful accessibility supports, and unrestricted delegation, which can create dependency. The AIMIL Inclusive Human-AI Information Judgement Model (AIMIL-IHIJ) operationalises this

idea through six recursive capabilities. Frame defines the research problem before selecting a tool. Engage uses AI purposefully and proportionately. Triangulate compares generated output with scholarly databases, original research, and authoritative sources. Trace reconstructs the evidence chain from generated statement to authentic record, full text, and relevant passage. Verify tests factual accuracy, citation identity, claim-evidence correspondence, methodological quality, currency, bias, and AI-induced transformation. Construct produces a human-authored, transparently attributed, and ethically defensible judgement. Across all six stages operate three safeguards: accessibility and learner agency, human epistemic oversight, and ethical responsibility.

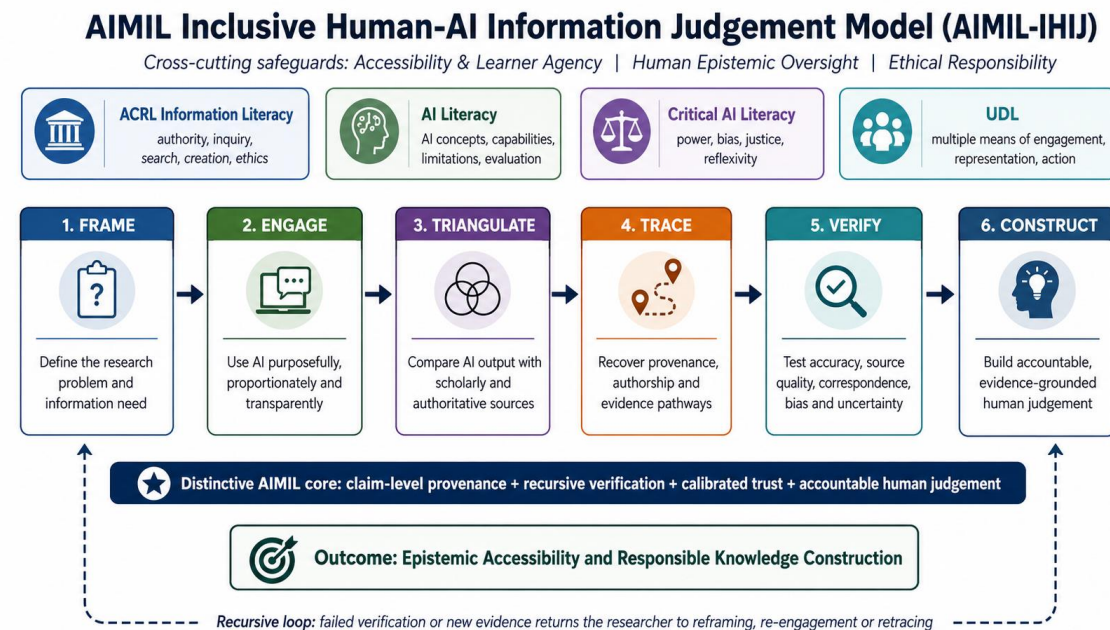


Figure 1. AIMIL Inclusive Human-AI Information Judgement Model (AIMIL-IHIJ)

### 3.4 Practice Grounding in the Current Normal

The pseudonymised internal report used as a practice vignette describes a contemporary university environment in which AI-enabled systems, coding, intelligent technologies, visual workflow displays, iterative testing, and industry-connected learning are already integrated into ordinary educational practice (Author, 2026). The value of this vignette is not evidential generalisation but contextual realism: higher

education increasingly operates in hybrid ecosystems where students learn with AI, automation, and external technology partners. The report also shows that digital sophistication does not remove the need for human guidance. For AIMIL, the implication is direct: the relevant question is no longer whether students will encounter AI, but how institutions help them retain verification, provenance awareness, and human judgement when AI is already part of the learning environment

### 3.5 Theoretical Propositions and Library Training Implications

AIMIL-IHIJ is intended to be empirically testable rather than purely descriptive. The following

propositions translate its central constructs into relationships that can be examined through performance-based assessments, quasi-experimental library interventions, mixed-method studies, and longitudinal designs.

Table 2. AIMIL-IHIJ constructs and theoretical propositions

| Construct                | Operational meaning                                                                  | Proposition                                                                                                                                         |
|--------------------------|--------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------|
| Framing competence       | Separates research problem from AI-support task                                      | P1. AIMIL-based training will improve detection of fabricated or misrepresented references compared with conventional search training alone.        |
| Provenance competence    | Authenticates source identity and reconstructs claim-to-source pathways              | P2. Provenance competence will positively predict claim-evidence correspondence.                                                                    |
| Triangulation competence | Compares AI output with independent scholarly or authoritative evidence              | P3. Triangulation competence will reduce uncritical acceptance of confident but unsupported AI outputs.                                             |
| Epistemic accessibility  | Enables access, understanding, tracing, evaluation and defence of information        | P4. Epistemic accessibility will positively predict research participation and self-efficacy among learners who use AI as an accessibility support. |
| Verification competence  | Tests factual, evidential, methodological, temporal, bias and transformation quality | P5. Verification competence will mediate the relationship between GenAI use and research effectiveness.                                             |
| Epistemic agency         | Retains final responsibility for accepting or rejecting claims                       | P6. Excessive delegation of evaluative tasks to GenAI will be negatively associated with epistemic agency.                                          |



| Construct                | Operational meaning                                       | Proposition                                                                                                                       |
|--------------------------|-----------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------|
| AIMIL training           | Builds recursive verification and calibrated trust        | P7. AIMIL training will moderate the relationship between frequency of GenAI use and epistemic dependency.                        |
| Accountable construction | Synthesises verified evidence transparently and ethically | P8. Accountable knowledge construction will be strongest when accessibility, human oversight and ethical responsibility co-occur. |

For academic libraries, these propositions imply a shift from one-shot tool demonstrations to repeated judgement practice. A compact AIMIL training sequence can ask learners to: define what the AI may assist with; identify claims requiring evidence; triangulate across databases and authoritative sources; trace AI-proposed references to authentic records and full text; compare generated summaries against original passages; detect lost qualifications or bias; and reconstruct a paragraph using only verified evidence. This aligns with emerging calls for library-led GenAI competencies while preserving the core information-literacy commitment to authority, inquiry, and ethical participation (Khailova et al., 2026; Kim, 2025).

For students with disabilities, delivery should be accessible by design: structured verification records, screen-reader-compatible documents, keyboard navigation, captioned demonstrations, flexible pacing, and multimodal explanations. Assessment should focus on demonstrated judgement rather than on whether AI was used. A learner who uses AI for simplification, speech-based interaction, or brainstorming should still be able to show provenance, claim-evidence correspondence, conceptual understanding and final human responsibility.

#### 4. Discussion

The central contribution of AIMIL is to move the educational debate from AI use to evidential accountability. Information literacy, AI literacy, critical AI literacy and UDL each address essential parts of the problem, but none alone specifies how a researcher should move from generated language back to traceable evidence and forward to a defensible human judgement. AIMIL fills that gap by making provenance, semantic correspondence and recursive verification explicit.

This reframing is especially relevant to special and inclusive education. Inclusive practice should neither prohibit technologies that reduce access barriers nor lower the evidential standards expected of learners. Instead, support mechanisms may vary while the epistemic standard remains stable. A student may use GenAI to simplify a difficult passage or generate search terms, but the resulting scholarly claim still

requires source verification and accountable interpretation. In this sense, AIMIL treats accessibility and rigour as mutually reinforcing rather than competing goals.

The model also clarifies what meaningful human oversight requires. Policy documents often call for a 'human in the loop', but oversight becomes symbolic if the person lacks the competence to challenge the system. AIMIL defines oversight as epistemic capability: the ability to reconstruct evidence, identify error, recognise uncertainty, and reject AI output when the evidential warrant is insufficient (European Commission, 2022; UNESCO, 2023, 2024).

The model remains conceptual and requires validation. The review is targeted rather than exhaustive, AI systems differ in their retrieval and citation functions, and disability experiences are heterogeneous. Future studies should test the propositions using objective outcomes such as fabricated-citation detection, provenance accuracy, claim-evidence correspondence, identification of unsupported claims, and explanation of uncertainty. Co-design with learners with disabilities will be essential before treating epistemic accessibility as a stable measurable construct.

#### 5. Conclusion

Generative AI is becoming part of the infrastructure of academic research. Its accessibility benefits are significant, but access without verification is insufficient. This paper developed AIMIL as a theory of responsible human judgement in AI-mediated information environments and proposed the AIMIL-IHIJ model for inclusive academic-library training. The six capabilities, Frame, Engage, Triangulate, Trace, Verify, and Construct, make provenance and accountable judgement explicit, while the cross-cutting safeguards of accessibility, human oversight and ethical responsibility preserve learner agency. The paper's distinctive contribution is epistemic accessibility: genuine participation in academic research requires not only access to information but also the capacity to determine where it came from, whether it deserves trust, and why it can be defended as scholarly knowledge.

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