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International Journal of Artificial Intelligence and Machine Learning

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Preparing Ai-Ready Information Science Graduates: Extending Foi-Aimil Through Reciprocal Experiential Benchmarking and The Ai/Ml Information Lifecycle

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Abstract
Artificial intelligence (AI) is transforming the competencies required of Information Science graduates as information discovery, knowledge organisation, research support, analytics and professional decision-making become increasingly AI-mediated. This paper extends Festival of Ideas (FOI)-based experiential pedagogy with AI-Mediated Information Literacy (AIMIL) as the FOI-AIMIL framework for developing AI-ready Information Science graduates through experiential learning, authentic assessment and governance-oriented practice. Using an exploratory qualitative case-study and theory-extension design, the study is informed by a pseudonymised analysis of an official reciprocal academic visit by a Malaysian Public University (MPU) to a Chinese Applied Technology University (CATU) in southeastern China in May 2026. Particular attention is given to an industry-integrated School of Information Technology ecosystem involving AI-enabled applications, coding, intelligent systems, software development, practical experimentation and embedded industry expertise. Evidence is coded as Observed, Reported, Documented, AI-Assisted or Inferred and interpreted through the six AIMIL capabilities of Frame, Engage, Triangulate, Trace, Verify and Construct. A complementary crosswalk maps these capabilities onto the AI/ML information lifecycle from data and model through output, human interpretation, evidence and decision, while treating AIMIL as a recursive governance layer rather than a substitute for technical model-development methodologies. The analysis generates five theoretically relevant mechanisms for graduate formation: authentic AI exposure, situated industry learning, cognitive infrastructure, epistemic debugging through recursive verification, and evidence-to-professional-practice translation. The paper proposes the FOI-AIMIL Reciprocal Experiential Intelligence Cycle and an AI-Ready Information Science Graduate profile integrating information intelligence, AI-mediated judgement, provenance and verification, AI/digital analytics, governance and professional adaptability. Five consolidated propositions are advanced for future empirical testing. The study argues that graduate readiness should not be defined by AI tool proficiency alone, but by the capacity to interrogate AI-mediated information, establish provenance, evaluate evidence, govern information responsibly and defend professional decisions. The framework offers a transferable basis for curriculum redesign, authentic assessment, academic library education and industry-university collaboration in the AI era.

Keywords: AI-Mediated Information Literacy, artificial intelligence, human-AI judgement, Information Science education, machine learning.

1. Introduction

Artificial intelligence has moved from a specialist computational domain into the everyday infrastructure of higher education and professional information work. Generative systems now mediate searching, summarisation, classification, recommendation, synthesis and writing, while machine-learning applications are increasingly embedded within library discovery tools, digital repositories, analytics platforms and knowledge-management environments. AI literacy has therefore become an educational requirement rather than an optional digital skill [1]-[5].

The implications are particularly consequential for Information Science education. Information Science has historically prepared graduates to discover, organise, evaluate, preserve, retrieve, communicate and govern information. AI does not remove these functions; it changes their epistemic conditions. A graduate may now encounter a machine-produced representation of a topic before encountering the source record itself. A retrieval system may rank information algorithmically. A generative interface may produce plausible but unsupported citations. An automated classification or recommendation system may conceal assumptions that would previously have been visible to a human intermediary. Higher education consequently requires graduates who can work with AI while retaining responsibility over the quality and consequences of information [6]-[10].

Recent research has begun to articulate AI literacy as a combination of technical understanding, application, critical evaluation and ethical awareness [11]-[14]. Within library and information science (LIS), this agenda has accelerated sharply. Studies published in 2024-2026 report the integration of generative AI into information-literacy instruction, the development of academic-library AI literacy programmes, emerging AI literacy measurement instruments for LIS students and librarians, and persistent curricular fragmentation in critical AI literacy [15]-[21]. These findings point to a disciplinary opportunity but also a gap: AI competence risks being framed as tool proficiency unless it is connected explicitly to provenance, verification, accountable judgement and professional governance.

AI-Mediated Information Literacy (AIMIL) addresses this gap by conceptualising information literacy as a recursive and ethically accountable practice in which human judgement remains responsible for claims passing through AI systems. Its six capabilities - Frame, Engage, Triangulate, Trace, Verify and Construct - move the learner from problem definition and purposeful interaction towards provenance reconstruction, evidential verification and accountable knowledge construction. FOI-AIMIL extends this principle into experiential pedagogy by integrating authentic experience, analytical reconstruction, AI-mediated scaffolding and governance-oriented assessment.

The present paper further extends FOI-AIMIL into the preparation of AI-ready Information Science graduates. The theoretical development is informed by a pseudonymised reciprocal benchmarking case involving a Malaysian Public University (MPU) and a Chinese Applied Technology University (CATU). The host environment provided direct exposure to an industry-integrated technology ecosystem involving AI-enabled systems, coding, application development, intelligent systems, hardware-software integration, testing and practical experimentation. The case is used not to evaluate the host university or to claim causal educational outcomes, but to examine what authentic exposure to such an ecosystem reveals about graduate capability in Information Science.

This study makes four contributions. First, it extends FOI-AIMIL from classroom experiential pedagogy to reciprocal experiential intelligence, explaining how external technological exposure can be converted into accountable educational and institutional learning. Second, it introduces an evidence-status protocol that separates observed, reported, documented, AI-assisted and inferred claims, thereby strengthening traceability in AI-related benchmarking. Third, it positions AIMIL as a recursive information-science and governance layer across the AI/ML information lifecycle, linking data, models and outputs to human interpretation, evidence and accountable decisions. Fourth, it translates this architecture into an AI-ready Information Science graduate capability profile, an authentic-assessment pathway and theoretically testable propositions.

The study addresses four research questions: (RQ1) What competencies are required for Information Science graduates to operate responsibly within AI-mediated professional and knowledge environments? (RQ2) How can FOI-AIMIL integrate experiential learning, information literacy and responsible AI practice within Information Science education? (RQ3) What lessons from an industry-integrated technological learning ecosystem are relevant to the development of AI-ready Information Science graduates? (RQ4) How can the AIMIL capabilities of Frame, Engage, Triangulate, Trace, Verify and Construct be translated into graduate competencies and authentic assessment?

2. Literature Review

2.1 AI Literacy and Human Judgement in Higher Education

AI literacy emerged initially as a competency construct concerned with understanding AI concepts, recognising applications and limitations, interacting effectively with AI and evaluating societal implications. Long and Magerko [1] framed AI literacy around competencies that allow non-specialists to critically evaluate and communicate with AI. Ng et al. [2] subsequently organised AI literacy around knowing and understanding AI, applying AI, evaluating and creating AI, and ethical awareness. A scoping review by Laupichler et al. [3] showed that higher and adult education research was expanding but remained conceptually diverse, while later work on AI literacy scales and user-oriented learning models confirmed that the construct encompasses cognitive, technical, evaluative and ethical dimensions [11], [12].

The arrival of generative AI intensified the problem of human judgement. Large language models can accelerate ideation, translation and explanation, but their fluent output can conceal fabricated references, semantic distortion and compressed uncertainty. Empirical studies have demonstrated citation fabrication and substantive reference errors in generative systems [22]-[24]. This creates a distinction between interface credibility and evidential credibility. Responsible use therefore requires users to verify sources independently, preserve provenance and distinguish transformation tasks from evidential tasks.

Policy frameworks reinforce this human-centred position. UNESCO's guidance for generative AI in education and research stresses human agency, transparency, inclusion and ethical use [7]. Its 2024 competency frameworks for students and teachers treat AI competence as more than operational skill by incorporating human-centred mindset, ethics and responsible creation [8], [9]. The European Commission similarly emphasises critical and ethical use of AI and data in education [10]. Across these frameworks, human accountability is not displaced by automation; it becomes a condition for responsible adoption.

2.2 AI Literacy in Library and Information Science Education

The LIS literature is moving quickly from general discussion towards discipline-specific competency design. Carroll and Borycz [15] demonstrated how large language models can be integrated into information-literacy instruction to support information retrieval and knowledge synthesis while still requiring critical evaluation. Chaudhuri and Terrones [16] reported the redesign of academic-library information-literacy initiatives in response to ChatGPT and related systems. LaFlamme [17] proposed a four-tier instructional model progressing from awareness and application to critical evaluation and ethical advocacy. Ali and Richardson's scoping review [18] found that academic libraries increasingly provide AI literacy workshops, LibGuides and instructional resources, but librarians themselves require continuing development.

The graduate-education dimension is becoming especially visible. Hossain and colleagues found uneven AI literacy among LIS students in South Asia and highlighted the importance of curriculum coverage, ethical competence and educational context [19], [20]. Montesi et al. [21] developed AILIS 1.0 specifically for LIS students and librarians, arguing that AI literacy in LIS should not be reduced to a simple extension of existing literacies. Bridges et al. [25] identified significant curricular fragmentation and a false dichotomy between technical and critical approaches in international LIS education. Their analysis suggests that future programmes need integrated models that combine technological understanding with professional values, critical judgement and social responsibility.

In 2026, Khailova et al. [26] articulated generative-AI information-literacy competencies aligned with the ACRL Framework, placing human oversight and disciplinary judgement at the centre. This development is important because it connects emerging AI practices to established information-literacy concepts such as authority, information creation, inquiry and strategic exploration. Academic libraries are therefore increasingly positioned not merely as providers of access but as sites for critical AI education and information stewardship [27], [28].

Related 2023-2025 work reinforces the need for critical rather than merely operational adoption. SWOT analyses and academic-integrity studies emphasise both educational opportunities and risks of over-dependence [29], [30]; ethics scholarship and policy reports highlight transparency, fairness and human responsibility [31]-[33]. Academic-library initiatives further show the value of interdisciplinary collaboration for responding to generative-AI information needs [34], while library-based AI literacy programmes demonstrate the continuing relevance of established information-literacy models [35]. These developments are consistent with the ACRL Framework's emphasis on authority, inquiry, information creation and strategic exploration [36], but they also reveal why AI-mediated provenance and verification require more explicit treatment.

Taken together, this literature reveals four unresolved tensions that motivate FOI-AIMIL. First, AI literacy is frequently framed as technical or operational capability, whereas professional practice also requires epistemic judgement over the quality of AI-mediated claims. Second, ethical awareness is often stated as a principle but is less often connected to auditable provenance and verification practices. Third, experiential exposure to AI-rich environments can encourage adoption without necessarily producing disciplined evidence evaluation. Fourth, existing competency approaches do not always connect AI outputs to the full information pathway through interpretation, evidence and accountable decision-making. FOI-AIMIL is positioned as a response to these tensions by integrating experiential exposure with recursive verification, provenance reconstruction and governance-oriented knowledge construction.

2.3 Experiential Learning, Authentic Assessment and Graduate Readiness

FOI-AIMIL also draws on experiential and situated theories of learning. Kolb's experiential learning cycle conceptualises learning as a recursive movement through concrete experience, reflective observation, abstract conceptualisation and active experimentation [37]. Situated learning locates knowledge within authentic communities of practice rather than treating learning as decontextualised acquisition [38]. Cognitive apprenticeship similarly foregrounds modelling, coaching, scaffolding and participation in expert practice [39]. These traditions remain relevant to AI education because technological competence develops through encounters with uncertain tasks, real workflows, professional standards and iterative problem solving.

Authentic assessment further strengthens this relationship. Wiggins [40] argued that assessment should require students to perform meaningful tasks resembling really intellectual or professional work. In AI-mediated environments, authenticity should include evidence traceability, AI-use disclosure, verification and the ability to defend decisions. FOI-AIMIL operationalises this orientation through experiential evidence, analytical reconstruction, bibliometric and visual analysis, AI declaration, rubric-based assessment and governance traceability.

Graduate readiness is therefore better understood as a capability configuration than as software familiarity. Information Science graduates need disciplinary foundations, digital and analytical capabilities, AI-mediated judgement, ethical governance and adaptability across changing organisational environments. Recent LIS studies support this direction by showing both the growing professional need for AI literacy and the unevenness of current training [18]-[21], [25]. The theoretical gap is a framework explaining how authentic technological exposure can be converted into verified Information Science judgement rather than simple imitation or tool adoption.

2.4 FOI-AIMIL as the Integrating Theoretical Lens

For clarity, FOI-AIMIL denotes the integration of Festival of Ideas (FOI) based experiential pedagogy with AI-Mediated Information Literacy (AIMIL). In its original Information Science implementation, FOI functions as an authentic field-based learning context in which students encounter live knowledge, research, innovation and professional information environments. AIMIL supplies the epistemic and governance layer that requires students to frame information problems, engage with human and AI-mediated sources, triangulate evidence, trace provenance, verify claims and construct defensible conclusions. Together, FOI-AIMIL links concrete experience with reflective and analytical reconstruction, AI-mediated scaffolding, and accountable assessment through evidence portfolios, AI-use transparency, rubrics and traceability [41], [42]. In this paper, FOI-AIMIL is treated as a transferable theoretical architecture rather than as an event-specific teaching intervention: the reciprocal benchmarking case provides the authentic experience, while AIMIL structures how that experience is converted into verified Information Science judgement and graduate capability.

FOI-AIMIL integrates five complementary traditions: experiential learning, situated learning, constructivist knowledge formation, information literacy and AIMIL. Its original educational implementation uses authentic field engagement as experiential input; observation and reflection as analytical processing; digital communication and AI as scaffolding; and formal documentation, rubrics, evidence portfolios and AI-use transparency as governance mechanisms. Published FOI-AIMIL studies report its use in undergraduate and postgraduate Information Science education and position it as a bridge between experiential learning and accountable AI-mediated scholarship [41], [42].

AIMIL adds an epistemic architecture to that model. Frame defines the question and evidential threshold. Engage structures purposeful interaction with people, systems and sources. Triangulate compares evidence channels. Trace reconstructs provenance. Verify tests authenticity, accuracy, currency and contextual fit. Construct produces a defensible human judgement. These capabilities are recursive: verification may reveal a need to reframe the problem or seek additional evidence. The present study applies this architecture to reciprocal experiential benchmarking and graduate development.

2.5 Mapping AIMIL to the AI/ML Information Lifecycle

To strengthen the connection between Information Science education and artificial intelligence and machine learning practice, AIMIL can be mapped onto an AI/ML information lifecycle comprising data, model, output, human interpretation, evidence and decision. The purpose of this mapping is not to present AIMIL as a substitute for technical model-development methodologies. Rather, it functions as an information-science and governance overlay that helps graduates interrogate how data and models produce outputs that later become evidence for human decisions. This orientation is consistent with human-centred and risk-aware AI guidance that emphasises data quality, transparency, explainability, evaluation, accountability and continuing risk management across the AI lifecycle [7], [9], [10], [31], [33], [43].

The mapping begins with Frame at the data stage, where the graduate asks what information problem is being addressed, what data are being used, where those data originate and whether their scope, quality and governance conditions are defensible. Engage aligns with the model stage by requiring purposeful interaction with model documentation, intended-use statements, system interfaces and known limitations. Triangulate is applied to model outputs by comparing generated, ranked or classified results with alternative systems, authoritative sources and independent evidence. Trace focuses on human interpretation by reconstructing the path from data and model to output and documenting where AI mediation enters the reasoning process. Verify examines whether the resulting claim is sufficiently accurate, current, contextually valid and robust to function as evidence. Construct addresses the decision stage, where information is translated into a defensible professional judgement accompanied by appropriate disclosure, governance controls and an auditable evidence trail.

For Information Science graduates, this lifecycle crosswalk makes machine learning relevant without requiring every graduate to become an ML engineer. It requires sufficient technical and informational understanding to question training-data provenance, model documentation, output uncertainty, algorithmic bias, explainability and downstream information governance. The central educational outcome is therefore the capacity to decide when an AI/ML output can legitimately move from computational result to professional evidence and, ultimately, to accountable action.

The stage-to-capability alignments in Table 1 are therefore heuristic rather than exclusive. Frame, Engage, Triangulate, Trace, Verify and Construct can recur at multiple points in the lifecycle: provenance may need to be traced at the data stage, model claims may require verification, outputs may require repeated triangulation, and decisions may trigger reframing. The crosswalk should consequently be read as a dominant alignment for teaching and analysis, with AIMIL operating recursively across the lifecycle rather than as a linear one-to-one sequence.

Table 1. Mapping AIMIL to the AI/ML information lifecycle

AI/ML lifecycle stage	**Information Science concern**	**AIMIL capability**	**Graduate interrogation and professional judgement**
Data	Provenance, representativeness, quality, rights and governance	Frame	Define the information problem; establish data origin, scope, purpose, limitations, permissions and governance conditions.
Model	Model purpose, documentation, assumptions, training/evaluation context and known limitations	Engage	Interrogate model documentation, intended use, system boundaries, interfaces, limitations and relevant performance evidence.
Output	Uncertainty, error, hallucination, ranking/classification effects and alternative explanations	Triangulate	Compare outputs with authoritative sources, independent evidence, alternative systems and contradictory findings.
Human interpretation	Explainability, contextual meaning, over-trust and hidden mediation	Trace	Reconstruct how data, model and output contribute to the claim; document where AI mediation enters the reasoning chain.
Evidence	Validity, currency, source integrity, robustness and contextual fit	Verify	Check whether claim-to-evidence links are authentic, current, sufficiently supported and appropriate for the professional context.
Decision	Accountability, fairness, privacy, downstream impact and auditability	Construct	Produce a defensible decision or information product with disclosure, governance controls, justification and an auditable evidence trail.

2.6 Human-in-the-Loop Evaluation and AI/ML Evidence Governance

For AI/ML-oriented professional practice, the critical transition is not merely from model to output but from output to evidence. An AI/ML system may produce a prediction, classification, ranking, recommendation or generated response, yet that computational result does not automatically constitute professionally usable evidence. Human-in-the-loop evaluation must consider the provenance and representativeness of data, the intended purpose and documented limitations of the model, uncertainty or error in outputs, contextual interpretation, fairness and privacy implications, and the consequences of downstream use [7], [9], [10], [31], [33], [43]. FOI-AIMIL contributes an Information Science perspective to this transition by requiring the user to reconstruct how a claim was produced, test it against independent evidence, disclose AI mediation where material, and justify the final decision. In this sense, the framework addresses the epistemic and governance conditions under which an AI/ML output may legitimately be treated as evidence rather than proposing a new machine-learning algorithm or model-development procedure.

3. Methodology

3.1 Research Design and Case Boundary

The study uses an exploratory qualitative case-study and theory-extension design. The empirical context was an official reciprocal academic visit in May 2026 between MPU, a Malaysian public university, and CATU, a vocationally and technologically oriented university in southeastern China. The author affiliation is reported in full for publication transparency, while the host institution, reciprocal-case identifiers, geographic particulars, commercial partners and individual host representatives are pseudonymised or generalised because the purpose of the paper is conceptual development rather than institutional evaluation.

The unit of analysis is the observed educational-technological ecosystem and the process through which reciprocal benchmarking observations were translated into Information Science graduate-development insights. No student-level outcome data from CATU are analysed, and the paper makes no claims regarding proprietary AI or machine-learning performance.

3.2 Data Sources

The evidence base comprises four source classes: (1) reflective field documentation produced after the reciprocal visit; (2) visual benchmarking material showing the host School of Information Technology's facilities, digital learning environments, AI-related spaces and industry integration; (3) institutional briefings and descriptions encountered during the visit; and (4) FOI-AIMIL/AIMIL theoretical documentation used to structure interpretation. The reciprocal-visit report records an immersive technology environment integrating real-world digital applications, AI ecosystems, software-development environments, practical experimentation and embedded industry expertise. Visual materials independently reinforce the presence of laboratories, digital ecosystems, AI and industry-integrated learning environments.

Because reflective field documentation combines direct observation, statements reported by hosts and later interpretation, the study introduces formal source/evidence coding protocol. The protocol prevents reported or inferred information from being presented as if directly observed and makes AI-assisted processing explicitly visible.

3.3 Source and Evidence Coding Protocol

Table 2. Source/evidence coding protocol for the pseudonymised reciprocal benchmarking case

Code	Evidence status	Definition	Permitted analytical use	Example in this study
O	Observed	Directly witnessed by the researcher during the visit or visible in source images.	May support descriptive findings when bounded to what was actually visible.	Laboratory layouts, workflow displays, student workspaces, digital and technology facilities.
R	Reported	Information communicated by host representatives, engineers or institutional personnel.	May be reported as an attributed explanation, not as independently verified fact.	Descriptions of how an industry partner supports platforms, training or technical activities.
D	Documented	Information recorded in formal visit materials, institutional documents, agreements or visual benchmarking records.	May support chronology, programme structure and documented institutional intentions.	Reciprocal visit purpose, collaboration history and documented visual benchmarking material.

Code	Evidence status	Definition	Permitted analytical use	Example in this study
A	AI-Assisted	AI used to support organisation, comparison, language refinement or thematic synthesis of already available evidence.	May assist analysis but cannot elevate weak evidence or create new empirical facts.	Grouping coded observations into graduate-capability themes; language refinement.
I	Inferred	Researcher interpretation derived from one or more O/R/D sources and theoretical analysis.	Must be stated as interpretation or proposition and remain open to empirical testing.	The concept of cognitive infrastructure and the proposed Reciprocal Experiential Intelligence Cycle.

3.4 Analytical Procedure

Analysis followed the six AIMIL capabilities and treated each substantive case statement as the analytical unit for evidential classification. Frame identified the educational problem: how authentic AI-intensive environments can inform Information Science graduate readiness. Engage organised direct and documentary engagement with the case. Triangulate compared field observations with visual documentation, institutional explanations and current literature. Trace assigned each substantive case statement an O/R/D/A/I evidence status at claim level, so that reported or inferred material was not elevated to direct observation. Verify limited claims to what the available evidence could support and tested transferability against Information Science educational needs. Construct synthesised verified observations into graduate-capability domains, the conceptual cycle and theoretical propositions. The protocol is intended to strengthen claim-level transparency rather than to imply statistical coding reliability or technical validation of the host's AI/ML systems.

The use of AI in manuscript preparation was restricted to analytical scaffolding and language support. AI-assisted processing did not substitute for source verification, did not create empirical observations and was treated as an A-coded analytical aid under the protocol above.

4. Findings

4.1 Authentic AI Exposure as Situated Professional Learning

The strongest observed pattern was the integration of digital technologies into practical learning environments rather than their treatment as isolated classroom topics. The host School of Information Technology combined AI-related systems, coding, application development, hardware-software integration, testing environments and project-oriented technological work. The significance for Information Science is not that every graduate should become a software engineer. Rather, graduates benefit when AI is encountered as part of authentic information and organisational workflows.

For Information Science programmes, this principle can be translated into curricular combinations such as AI plus information retrieval, AI plus metadata, AI plus bibliometrics, AI plus digital libraries, AI plus records and information governance, AI plus digital preservation, and AI plus knowledge management. Such integration allows students to judge AI within disciplinary contexts instead of learning AI as a detached toolset.

4.2 Embedded Industry Expertise and the Academic-Professional Boundary

A second pattern was the presence of industry expertise within the educational ecosystem. Host explanations and the reciprocal report indicated that engineers from a major global ICT industry partner were stationed within the technology environment and supported applied learning. Students were exposed to coding, prototype development, testing and implementation under industry-oriented supervision. This reduces the temporal gap between rapidly changing technological practice and formal university curricula.

The finding also raises a governance requirement. Industry expertise should supplement academic judgement rather than determine it. Information Science programmes must retain authority over curriculum, data governance, ethics, vendor claims, academic independence and professional values. FOI-AIMIL therefore interprets industry integration as a situated-learning asset only when accompanied by institutional epistemic oversight.

4.3 Learning Spaces as Cognitive Infrastructure

Visual workflow displays and industrial process diagrams were a recurring feature of the observed environment. Coding structures, technology architectures, production pathways and workflow procedures were made visible within laboratories and surrounding spaces. The physical environment therefore functioned as cognitive infrastructure: students were continuously exposed to representations of how systems, processes and technologies relate.

The Information Science analogue would be learning spaces that externalise information lifecycles, metadata architectures, knowledge graphs, provenance chains, digital-preservation workflows, research-data pipelines and algorithmic decision pathways. AI readiness is strengthened when students can see relationships between information, systems and accountability rather than treating technologies as black boxes.

4.4 Recursive Verification, Debugging and Epistemic Practice

The observed technological culture also normalised trial, error, debugging, testing and revision. This practice has a direct epistemic parallel in AIMIL. When a generative system produces an uncertain claim, the responsible response is not immediate acceptance or blanket rejection; it is tracing and verification. In both software development and information judgement, error becomes a diagnostic signal that initiates further investigation.

This structural similarity suggests that verification should be taught as a core professional practice rather than as a warning attached to AI use. The paper terms this recursive practice epistemic debugging: the identification, tracing and correction of weaknesses in AI-mediated claims through source reconstruction, triangulation, contextual checking and verification. Students can be trained to identify claims that require evidence, reconstruct source chains, test currency and contextual fit, and document why an AI-mediated output was accepted, modified or rejected. Epistemic debugging therefore converts error or uncertainty from a reason for passive distrust into a diagnostic signal for disciplined information judgement.

4.5 From Technological Observation to Graduate Capability

The reciprocal case became educationally useful only after observations were translated into disciplinary capability. The relevant question was not which laboratories should be copied, but what forms of reasoning, verification, professional interaction and technological adaptability the environment made possible. This shift from object benchmarking to capability benchmarking is central to FOI-AIMIL.

Six graduate domains emerged from the synthesis: Information Intelligence; AI-Mediated Judgement; Provenance and Verification; AI, Digital and Analytical Capability; Governance and Ethics; and Professional Adaptability. These domains form the outcome layer of the proposed conceptual framework.

Table 3. FOI-AIMIL AI-ready Information Science graduate capability domains

Domain	Graduate capability	Indicative evidence in assessment
Information Intelligence	Discover, organise, interpret and synthesise complex information.	Search strategy, synthesis memo, evidence map, information architecture.
AI-Mediated Judgement	Critically evaluate AI-generated and AI-mediated information.	AI output critique, comparative evaluation, justified acceptance/rejection.
Provenance and Verification	Trace claims and establish evidential authenticity, currency and contextual fit.	Claim-source audit, provenance chain, DOI/source verification, semantic checking.
AI, Digital and Analytical Capability	Use AI systems, analytics, bibliometrics and digital tools with sufficient understanding of model purpose, limitations, uncertainty and disciplinary context.	Data visualisation, bibliometric exercise, model/output critique, workflow analysis, tool comparison.
Governance and Ethics	Address privacy, transparency, integrity, accountability and responsible AI use.	AI declaration, governance memo, risk assessment, ethical justification.

Domain	Graduate capability	Indicative evidence in assessment
Professional Adaptability	Transfer Information Science judgement across new technological and organisational settings.	Industry case analysis, reflective portfolio, benchmarking-to-action proposal.

5. Foi-Aimil Reciprocal Experiential Intelligence Cycle

The case supports an extension of FOI-AIMIL from student experiential learning to reciprocal experiential intelligence. The proposed cycle explains how an authentic external environment can become a source of graduate-development insight without collapsing into technological imitation. It preserves the six AIMIL capabilities while adding an explicit transition from experiential benchmarking to professional and institutional learning.

Frame establishes the educational question and evidential threshold. Engage places learners or academic observers inside authentic technological and professional environments. Triangulate compares direct observation with documents, expert explanations, scholarship and, where appropriate, AI-assisted synthesis. Trace reconstructs the provenance of every material claim. Verify tests authenticity, context, currency, transferability and governance fit. Construct produces defensible human knowledge that can inform curriculum, assessment or pilot implementation. The cycle remains recursive: new evidence may require reframing or renewed engagement.

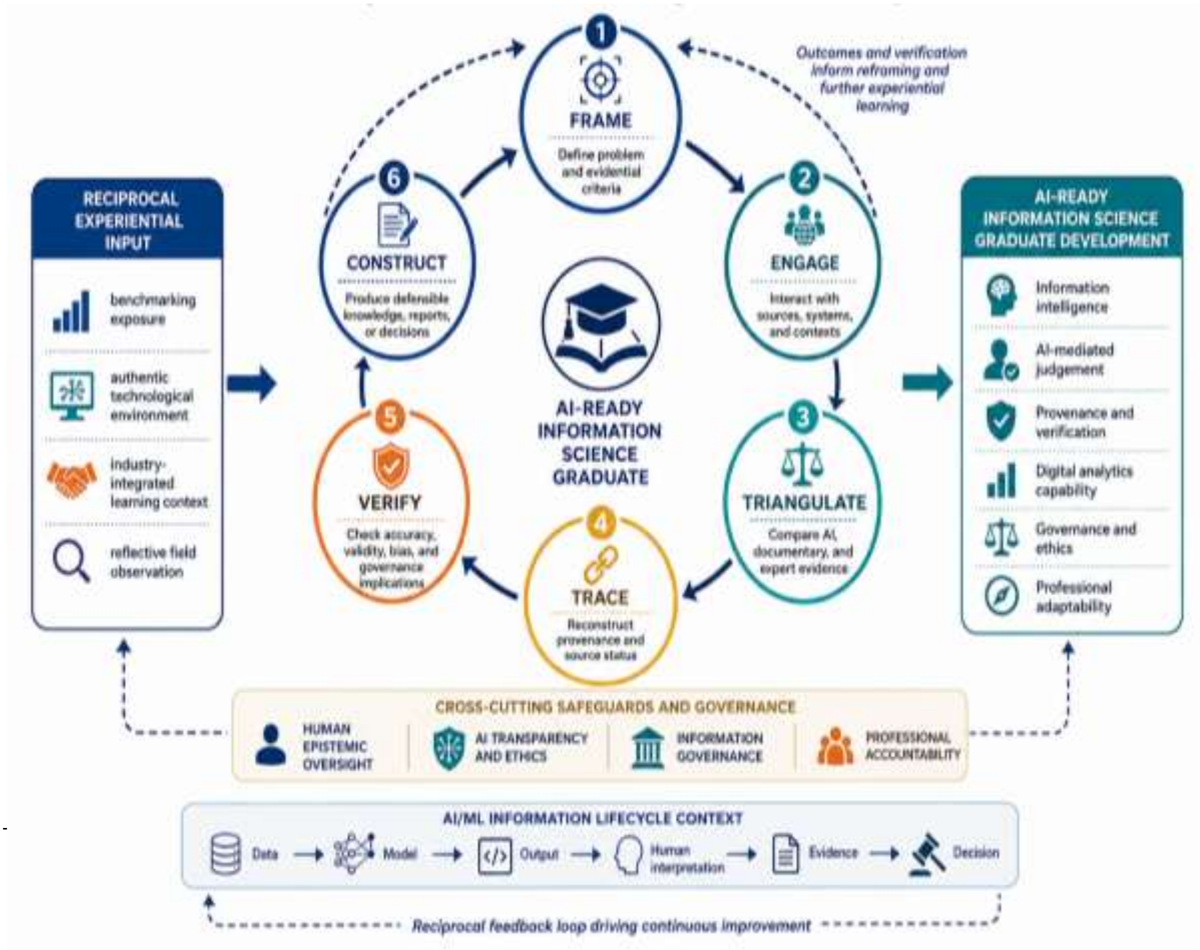
Fig. 1. FOI-AIMIL Reciprocal Experiential Intelligence Cycle for AI-ready Information Science graduate development.

6. Theoretical Propositions

P1. Authentic exposure to AI-enabled information environments strengthens the transfer between Information Science disciplinary knowledge and emerging professional practice when that exposure is analytically reconstructed rather than merely observed.

P2. AI readiness is stronger when technological capability is combined with information evaluation, provenance, verification and epistemic debugging than when competence is defined primarily by tool operation.

P3. Experiential learning strengthens AI-mediated information judgement when learners recursively Frame, Engage, Triangulate, Trace, Verify and Construct claims through evidence, reflection and



disciplinary theory.
P4. Industry-integrated learning and governance-oriented authentic assessment contribute to graduate readiness when academic independence, AI-use transparency, evidence traceability, ethical reasoning and institutional accountability are preserved.
P5. The professional identity of AI-ready Information Science graduates increasingly shifts from information intermediary towards AI-mediated information steward, evaluator and knowledge-governance professional capable of accountable decision-making across changing technological environments.

7. Discussion

7.1 From Tool Competence to AI-Mediated Information Stewardship

The findings support a shift in the educational identity of Information Science. Graduates should not be trained merely to perform information tasks that AI can increasingly automate. Their distinctive professional value lies in defining information problems, evaluating authority, tracing provenance, interpreting context, governing access, identifying bias, protecting privacy and defending decisions. This is consistent with current LIS scholarship that increasingly treats librarians and information professionals as AI literacy educators and ethical information stewards [17], [18], [25]-[28].
The proposed graduate profile therefore reframes employability. AI-ready Information Science graduates may work as research-intelligence specialists, digital knowledge analysts, AI-enabled librarians, information-governance professionals, research-data specialists, digital curators, metadata specialists, information-integrity analysts and AI-governance support professionals. Exact occupational labels will change; the more durable competency combination is Information Science plus AI capability plus verification plus analytics plus governance plus professional judgement.
Relative to existing AI-literacy and competency approaches, the distinctive contribution of FOI-AIMIL is not a claim to replace them but to connect dimensions that are often treated separately. UNESCO and related frameworks foreground human-centred, ethical and responsible AI competence [7]-[10]; emerging LIS models strengthen discipline-specific AI literacy and critical evaluation [17]-[21], [25]-[28]; and the ACRL tradition provides a mature basis for authority, inquiry and strategic exploration [36]. FOI-AIMIL adds an explicitly recursive provenance-to-decision architecture in which authentic experience is reconstructed through claim-level evidence status, AI mediation is made visible, and professional conclusions must remain auditable and defensible. Its theoretical emphasis is therefore the conversion of AI-mediated output into accountable human judgement.

7.2 Curriculum Implications

Curriculum redesign should embed AI across disciplinary subjects rather than confining it to a single emerging-technologies module. In information retrieval, students can compare database search with generative discovery and verify the provenance of returned claims. In metadata and knowledge organisation, they can evaluate automated description and classification. In bibliometrics and research analytics, they can examine AI-supported interpretation while checking underlying datasets and indicators. In records and information governance, they can analyse privacy, accountability, retention and auditability. In digital libraries and preservation, they can evaluate how intelligent automation affects authenticity and long-term stewardship.

FOI-AIMIL also suggests a change in assessment design. Assignments should require students to declare AI use, identify which parts of a task were AI-assisted, retain evidence trails and justify verification decisions. The purpose is not surveillance of tool use but development of professional accountability. When AI is embedded in workplaces, graduates will need to explain how outputs were produced and why particular information was trusted.

7.3 Implications for Experiential and Industry-Integrated Learning

The pseudonymised reciprocal case illustrates the educational value of technologically immersive environments where students encounter real systems, workflows and professional expertise. Information Science programmes can adapt this principle through industry-linked projects, library-technology laboratories, research-data collaborations, digital-curation studios, AI-assisted reference simulations and benchmarking visits. The critical condition is that experience must be analytically reconstructed. Without tracing and verification, experiential exposure risks becoming descriptive enthusiasm rather than learning.
Reciprocal international benchmarking can also contribute to graduate development when visits are designed around questions and evidence rather than ceremonial activity. The proposed coding protocol

and cycle provide a way to convert observation into auditable institutional learning. This is particularly useful when universities examine fast-moving AI ecosystems where vendor demonstrations, institutional narratives and visible infrastructure can otherwise be conflated with proven educational effectiveness.

8. Practical Application Model

Table 4. FOI-AIMIL implementation pathway for Information Science programmes

AIMIL stage	Curriculum action	Student evidence	Graduate outcome	Assessment criterion
Frame	Define an authentic AI-mediated information problem.	Problem statement and evidential criteria.	Strategic problem framing.	Clarity of problem definition and appropriateness of evidential threshold.
Engage	Use databases, AI systems, professional contexts and/or field environments.	Search logs, observation notes, system outputs.	Purposeful human-AI interaction.	Purposeful source/system selection and transparent interaction record.
Triangulate	Compare AI output with scholarly, documentary and expert evidence.	Comparison matrix and contradiction log.	Calibrated information judgement.	Quality of comparison, contradiction recognition and evidential calibration.
Trace	Map claim-to-source provenance and distinguish source status.	Provenance map and O/R/D/A/I coding.	Traceability and source accountability.	Completeness and accuracy of claim-to-source and AI-mediation provenance.
Verify	Check authenticity, meaning, currency, bias and governance implications.	Verification memo and risk assessment.	Evidence-based professional judgement.	Authenticity, currency, contextual validity, uncertainty and governance assessment.
Construct	Produce a defensible information product or decision.	Analytical report, dashboard, policy brief or portfolio.	Accountable knowledge construction.	Defensibility, disclosure, accountability and evidence-based justification of the final product or decision.

A practical implementation can therefore begin with one AI-mediated authentic assessment in an existing course rather than a wholesale curriculum redesign. The important design requirement is that students cannot obtain full credit merely by producing an AI-assisted output. Credit must depend on framing, evidence, provenance, verification, governance and the ability to defend the final judgement.

9. Limitations And Future Research

The study is theoretically generative rather than evaluative. It is based on one reciprocal benchmarking episode and does not measure the learning outcomes of students at the host institution. Observations were bounded to environments available during the official visit and should not be interpreted as a technical audit of the host university's AI or machine-learning infrastructure. The pseudonymisation strategy also reduces contextual specificity in order to protect institutional and commercial identities. As with reflective case research, interpretation is shaped by the researcher's observational position and by the selection of environments, briefings and materials available during the visit. The O/R/D/A/I protocol improves transparency about evidential status but does not remove interpretive judgement or establish causal educational effects.

The framework requires empirical testing. Future research should operationalise the six graduate-capability domains and validate an AI-Ready Information Science Graduate scale across students, graduates, employers and educators. Comparative studies could examine whether programmes using FOI-AIMIL-style authentic assessment demonstrate stronger provenance behaviour, verification accuracy, ethical reasoning and professional adaptability. Longitudinal work could test whether reciprocal experiential intelligence produces more sustainable curriculum innovation than conventional benchmarking reports.

A further research direction is the relationship between AIMIL and specific machine-learning workflows. The lifecycle crosswalk proposed in Section 2.5 provides a starting point by connecting Data, Model, Output, Human interpretation, Evidence and Decision with Frame, Engage, Triangulate, Trace, Verify and Construct. Information Science students do not necessarily need to become ML engineers, but they do require sufficient technical understanding to interrogate training-data provenance, model documentation, classification logic, output uncertainty, bias, explainability and system governance. Future interdisciplinary studies could test whether this crosswalk improves students' ability to evaluate model documentation, evidence quality, explainability claims and downstream information risk [43].

10. Conclusion

Artificial intelligence does not make Information Science education less relevant. It relocates the discipline's value from information access alone towards accountable judgement over AI-mediated information. The pseudonymised reciprocal case demonstrates the educational potential of authentic, technologically rich and industry-integrated environments, but also shows why observation must be processed critically before it becomes curriculum or strategy.

FOI-AIMIL provides that processing architecture. Through Frame, Engage, Triangulate, Trace, Verify and Construct, experience is converted into defensible knowledge. The proposed Reciprocal Experiential Intelligence Cycle extends this logic from classroom experiential learning to benchmarking and graduate development, while the source/evidence coding protocol protects the distinction between what was observed, reported, documented, AI-assisted and inferred.

The resulting AI-ready Information Science graduate is not defined simply by the ability to operate AI applications. Such a graduate should be able to discover intelligently, interrogate critically, trace provenance, perform epistemic debugging, verify systematically, govern responsibly and construct knowledge accountably within human-AI environments. The central contribution of FOI-AIMIL is therefore an accountable pathway from AI-mediated output to professional evidence and decision: a combination of disciplinary expertise, technological adaptability and human epistemic responsibility that can remain durable even as specific AI tools and model architectures change.

11. ACKNOWLEDGEMENTS

The authors acknowledge the institutional colleagues and host representatives whose professional engagement made the reciprocal academic visit possible. The host institution, commercial partner and individual host identities associated with the empirical case have been pseudonymised or generalised for publication.

DECLARATIONS

Funding: No external funding was received for this conceptual and qualitative case study.

Conflict of interest: The authors declare no conflict of interest.

Ethics: The study analyses reflective institutional observation and documentary materials arising from an official academic engagement. It involved no experimental intervention and no identifiable participant-level research data. Institutional, geographic, individual and commercial identifiers in the case have been pseudonymised or generalised.

Data availability: Underlying institutional documents contain potentially identifying information and are not publicly deposited. Relevant evidence is reported in aggregated and pseudonymised form within the manuscript.

Generative AI disclosure: AI-assisted tools were used for analytical organisation and language refinement. All substantive claims were verified against source materials and cited literature. AI assistance did not generate empirical observations, and responsibility for the manuscript remains with the authors.

References

[1] D. Long and B. Magerko, 'What is AI literacy? Competencies and design considerations,' Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems, pp. 1-16, 2020. doi:10.1145/3313831.3376727.
[2] D. T. K. Ng, J. K. L. Leung, S. K. W. Chu, and M. S. Qiao, 'Conceptualizing AI literacy: An exploratory review,' Computers and Education: Artificial Intelligence, vol. 2, 100041, 2021. doi:10.1016/j.caeai.2021.100041.
[3] M. C. Laupichler, A. Aster, J. Schirch, and T. Raupach, 'Artificial intelligence literacy in higher and adult education: A scoping literature review,' Computers and Education: Artificial Intelligence, vol. 3, 100101, 2022. doi:10.1016/j.caeai.2022.100101.
[4] H. Crompton and D. Burke, 'Artificial intelligence in higher education: The state of the field,' International Journal of Educational Technology in Higher Education, vol. 20, article 22, 2023. doi:10.1186/s41239-023-00392-8.
[5] Y. K. Dwivedi, N. Kshetri, L. Hughes, et al., 'So what if ChatGPT wrote it? Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy,' International Journal of Information Management, vol. 71, 102642, 2023. doi:10.1016/j.ijinfomgt.2023.102642.
[6] E. Kasneci, K. Sessler, S. Kuechemann, et al., 'ChatGPT for good? On opportunities and challenges of large language models for education,' Learning and Individual Differences, vol. 103, 102274, 2023. doi:10.1016/j.lindif.2023.102274.
[7] F. Miao and W. Holmes, Guidance for Generative AI in Education and Research. Paris: UNESCO, 2023. doi:10.54675/EWZM9535.
[8] F. Miao, K. Shiohira, and N. Lao, AI Competency Framework for Students. Paris: UNESCO, 2024. doi:10.54675/JKJB9835.
[9] F. Miao and M. Cukurova, AI Competency Framework for Teachers. Paris: UNESCO, 2024. doi:10.54675/ZJTE2084.
[10] Directorate-General for Education, Youth, Sport and Culture, European Commission, Ethical Guidelines on the Use of Artificial Intelligence (AI) and Data in Teaching and Learning for Educators. Luxembourg: Publications Office of the European Union, 2022. doi:10.2766/153756.
[11] T. Lintner, 'A systematic review of AI literacy scales,' npj Science of Learning, vol. 9, 50, 2024. doi:10.1038/s41539-024-00264-4.
[12] M. Pinski and A. Benlian, 'AI literacy for users: A comprehensive review and future research directions of learning methods, components, and effects,' Computers in Human Behavior: Artificial Humans, vol. 2, no. 1, 100062, 2024. doi:10.1016/j.chbah.2024.100062.
[13] A. Veldhuis, P. Y. Lo, S. Kenny, and A. N. Antle, 'Critical artificial intelligence literacy: A scoping review and framework synthesis,' International Journal of Child-Computer Interaction, vol. 43, 100708, 2025. doi:10.1016/j.ijcci.2024.100708.
[14] T. K. F. Chiu, Z. Ahmad, M. Ismailov, and I. T. Sanusi, 'What are artificial intelligence literacy and competency? A comprehensive framework to support them,' Computers and Education Open, vol. 6, 100171, 2024. doi:10.1016/j.caeo.2024.100171.
[15] A. J. Carroll and J. Borycz, 'Integrating large language models and generative artificial intelligence tools into information literacy instruction,' The Journal of Academic Librarianship, vol. 50, no. 4, 102899, 2024. doi:10.1016/j.acalib.2024.102899.
[16] J. Chaudhuri and L. Terrones, 'Reshaping academic library information literacy programs in the advent of ChatGPT and other generative AI technologies,' Internet Reference Services Quarterly, vol. 29, no. 1, pp. 1-25, 2025. doi:10.1080/10875301.2024.2400132.
[17] K. A. LaFlamme, 'Scaffolding AI literacy: An instructional model for academic librarianship,' The Journal of Academic Librarianship, vol. 51, no. 3, 103041, 2025. doi:10.1016/j.acalib.2025.103041.
[18] M. Y. Ali and J. Richardson, 'AI literacy guidelines and policies for academic libraries: A scoping review,' IFLA Journal, vol. 51, no. 3, pp. 588-599, 2025. doi:10.1177/03400352251321192.
[19] Z. Hossain, M. S. Biswas, and G. Khan, 'AI literacy of library and information science students: A study of Bangladesh, India and Pakistan,' Journal of Librarianship and Information Science, vol. 58, no. 1, pp. 285-299, 2026. doi:10.1177/09610006241309323.
[20] Z. Hossain, M. S. Biswas, N. A. Khan, and G. Khan, 'Artificial intelligence literacy among South Asian library and information science students: Socio-demographic influences and educational implications,' IFLA Journal, vol. 51, no. 3, pp. 629-646, 2025. doi:10.1177/03400352251331468.
[21] M. Montesi, B. Alvarez Bornstein, N. Bautista Puig, M. Blazquez Ochando, and A. Sanchez Diez, 'AILIS 1.0: A new framework to measure AI literacy in library and information science (LIS),' The Journal of Academic Librarianship, vol. 51, no. 5, 103118, 2025. doi:10.1016/j.acalib.2025.103118.

[22] W. H. Walters and E. I. Wilder, 'Fabrication and errors in the bibliographic citations generated by ChatGPT,' Scientific Reports, vol. 13, 14045, 2023. doi:10.1038/s41598-023-41032-5.
[23] J. Gravel, M. D'Amours-Gravel, and E. Osmanlliu, 'Learning to fake it: Limited responses and fabricated references provided by ChatGPT for medical questions,' Mayo Clinic Proceedings: Digital Health, vol. 1, no. 3, pp. 226-234, 2023. doi:10.1016/j.mcpdig.2023.05.004.
[24] A. McGowan, Y. Gui, M. Dobbs, et al., 'ChatGPT and Bard exhibit spontaneous citation fabrication during psychiatry literature search,' Psychiatry Research, vol. 326, 115334, 2023. doi:10.1016/j.psychres.2023.115334.
[25] L. Bridges, C. Lopezosa, M. Centelles Velilla, and N. Ferran-Ferrer, 'Moving towards critical AI literacy in LIS education: A scoping review and syllabi analysis,' The Electronic Library, vol. 43, no. 5, pp. 798-817, 2025. doi:10.1108/EL-06-2025-0224.
[26] L. Khailova, M. N. Wathen, and M. S. Jones, 'Articulating generative AI information literacy competencies: An ACRL Framework-driven model for academic libraries,' Journal of Information Literacy, vol. 20, no. 1, pp. 189-207, 2026. doi:10.11645/20.1.883.
[27] J. Kim, 'Academic library with generative AI: From passive information providers to proactive knowledge facilitators,' Publications, vol. 13, no. 3, 37, 2025. doi:10.3390/publications13030037.
[28] G. Demir, 'Artificial Intelligence Literacy: A new paradigm for libraries,' Information World, vol. 26, no. 1, pp. 183-222, 2025. doi:10.15612/BD.2025.803.
[29] M. Farrokhnia, S. K. Banihashem, O. Noroozi, and A. Wals, 'A SWOT analysis of ChatGPT: Implications for educational practice and research,' Innovations in Education and Teaching International, vol. 61, no. 3, pp. 460-474, 2024. doi:10.1080/14703297.2023.2195846.
[30] M. Perkins, 'Academic integrity considerations of AI large language models in the post-pandemic era: ChatGPT and beyond,' Journal of University Teaching & Learning Practice, vol. 20, no. 2, 2023. doi:10.53761/1.20.02.07.
[31] A. Nguyen, H. N. Ngo, Y. Hong, B. Dang, and B. P. T. Nguyen, 'Ethical principles for artificial intelligence in education,' Education and Information Technologies, vol. 28, pp. 4221-4241, 2023. doi:10.1007/s10639-022-11316-w.
[32] Office of Educational Technology, Artificial Intelligence and the Future of Teaching and Learning: Insights and Recommendations. Washington, DC: U.S. Department of Education, 2023.
[33] European Parliament and Council of the European Union, Regulation (EU) 2024/1689 Laying Down Harmonised Rules on Artificial Intelligence (Artificial Intelligence Act). Official Journal of the European Union, 2024.
[34] E. Fruehauf, A. Beman-Cavallaro, and L. Schmidt, 'Developing a foundation for the informational needs of generative AI users through the means of established interdisciplinary relationships,' The Journal of Academic Librarianship, vol. 50, no. 3, 102876, 2024. doi:10.1016/j.acalib.2024.102876.
[35] E. K. C. Wong and D. K. W. Chiu, 'AI literacy instruction program in international school libraries: A qualitative study under the lens of the Big Six Information Literacy model,' Journal of Librarianship and Information Science, vol. 58, no. 2, pp. 926-944, 2026. doi:10.1177/09610006251331977.
[36] Association of College and Research Libraries, Framework for Information Literacy for Higher Education. Chicago: American Library Association, 2016.
[37] D. A. Kolb, Experiential Learning: Experience as the Source of Learning and Development. Englewood Cliffs, NJ: Prentice Hall, 1984.
[38] J. Lave and E. Wenger, Situated Learning: Legitimate Peripheral Participation. Cambridge: Cambridge University Press, 1991. doi:10.1017/CBO9780511815355.
[39] A. Collins, J. S. Brown, and S. E. Newman, 'Cognitive apprenticeship: Teaching the crafts of reading, writing, and mathematics,' in Knowing, Learning, and Instruction, L. B. Resnick, Ed. Hillsdale, NJ: Lawrence Erlbaum Associates, 1989, pp. 453-494.
[40] G. Wiggins, 'The case for authentic assessment,' Practical Assessment, Research & Evaluation, vol. 2, article 2, pp. 1-3, 1990. doi:10.7275/ffb1-mm19.
[41] S. A. Ismail, 'FOI-based experiential pedagogy in information competency education in the era of digital and AI-mediated learning,' International Journal of Academic Research in Progressive Education and Development, vol. 15, no. 2, pp. 971-981, 2026. doi:10.6007/IJARPED/v15-i2/28175.
[42] S. A. Ismail, A. Hadiapurwa, and M. H. Ahsan, 'From procedural dependency to scholarly autonomy: Evaluating the impact of the FOI-AIMIL authentic assessment framework on postgraduate information science students,' International Journal of Research and Innovation in Social Science, vol. 10, no. 26, pp. 6507-6527, 2026. doi:10.47772/IJRISS.2026.1026EDU0477.
[43] E. Tabassi, Artificial Intelligence Risk Management Framework (AI RMF 1.0), NIST AI 100-1. Gaithersburg, MD: National Institute of Standards and Technology, 2023. doi:10.6028/NIST.AI.100-1.