

RESEARCH ARTICLE

# AI Literacy as an Emerging Competency for Students in Twenty-First-Century Higher Education

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ABSTRACT

Artificial intelligence is changing the intellectual work expected of university students by making automated generation, analysis, prediction, and decision support increasingly accessible within everyday learning. The resulting challenge is no longer limited to whether students can operate AI tools, but whether they can understand how such systems work, evaluate their outputs, recognise limitations, make ethical judgements, and use AI without surrendering academic responsibility. This conceptual review examines AI literacy as an emerging higher education competency that integrates conceptual knowledge, applied interaction, critical verification, ethical reasoning, and adaptive learning. Drawing on AI literacy scholarship, research on generative AI in education, digital capability, technology adoption, and student learning, the analysis identifies a central tension between rapid tool adoption and slower development of informed judgement. Students may become frequent AI users while remaining uncertain about model limitations, hallucination, bias, privacy, authorship, evidence quality, and appropriate disclosure. The review therefore positions AI literacy as a multidimensional educational capability rather than a narrow technical skill. It argues that universities should embed AI literacy across disciplines through experiential learning, evidence verification, explicit ethical guidance, inclusive access, and assessment designs that preserve meaningful student thinking. The resulting framework connects individual competency with institutional responsibility and explains how higher education can develop graduates who use AI productively, critically, transparently, and with sufficient intellectual independence to adapt as artificial intelligence continues to evolve.

**Keywords:** Literacy, Intelligence, Competency, Ethics, Education

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## 1. INTRODUCTION

Artificial intelligence now occupies a visible place in everyday university learning, changing how students access information, develop ideas, and complete academic tasks. Generative systems can now produce explanations, summaries, code, images, calculations, feedback, and draft arguments within seconds, placing AI directly inside ordinary academic work. This accessibility changes the meaning of digital competence because students can obtain sophisticated outputs without necessarily understanding the processes, assumptions, or limitations behind them. Long and Magerko (2020) conceptualise AI literacy through competencies that support informed interaction and critical evaluation, while Ng et al. (2021) emphasise understanding, use, evaluation, and ethical awareness. These foundations suggest that higher education cannot equate frequent tool use with genuine competence. Students need to know what AI can and cannot infer, how data and models shape results, why generated content may be plausible but wrong, and when human judgement must override automated assistance. The challenge has become more urgent as generative AI is embedded in writing, research, problem solving, and decision support. Zhao et al. (2024) show that students already integrate ChatGPT into wider digital writing practices, often with concerns about accuracy, plagiarism, and dependence. AI literacy therefore emerges as a core educational requirement for preserving intellectual agency while enabling productive technological participation. The deeper implication is that effective AI use depends on calibrated confidence: students need enough confidence to experiment, but also enough scepticism to verify claims, question assumptions, and acknowledge uncertainty.

AI literacy should be treated as an integrated educational capability rather than as a collection of disconnected technical skills. Conceptual knowledge enables students to distinguish statistical pattern generation from human understanding, applied competence supports purposeful interaction with AI systems, critical evaluation allows outputs to be tested against evidence, and ethical judgement guides decisions involving attribution, privacy, fairness, and responsibility. These dimensions are interdependent. A student who can produce an effective prompt but cannot verify the answer remains vulnerable to misinformation, while a student who understands model limitations but lacks practical experience may struggle to apply that knowledge in authentic academic tasks. Evidence from higher education supports this integrated view. Hornberger et al. (2023) found substantial variation in university students' AI knowledge, particularly across technical background and prior experience, and Mansoor et al. (2024) identified differences in AI literacy across national and academic contexts. The same pattern is visible in wider digital capability research, where technology adoption creates value only when users possess the knowledge and judgement required to apply it meaningfully (Yusof, 2025a). For universities, the strategic implication is clear: AI literacy should combine knowledge, practice, verification, and ethics so that students can use intelligent systems without confusing technological fluency with dependable academic competence. Such capability is increasingly relevant to employability because graduates are likely to work in environments where human judgement and automated systems operate together rather than as separate forms of work.

Recent scholarship presents AI literacy as a necessary response to the evolving relationship among students, knowledge, and automated systems. Laupichler et al. (2022) show that higher and adult education research has begun to identify recurring themes in AI literacy teaching, but also note continuing uncertainty about definitions, curriculum content, and validated assessment. More recent

empirical work indicates that student competence is uneven rather than naturally developing through exposure. Asio (2024) reports meaningful variation in AI literacy, self-efficacy, and self-competence among college students, while Tzirides et al. (2024) demonstrate that structured experience with generative AI can strengthen students' ability to understand and critically assess AI applications. These findings align with evidence that hands-on educational activities can develop broader learner capability when practical experience is connected to reflection and follow-up learning (Kamarudin et al., 2025). A strong AI literacy agenda should therefore avoid two extremes: purely technical instruction that overlooks educational purpose and purely policy-based guidance that tells students what is prohibited without teaching them how to make sound decisions. The more productive position is developmental. Students should encounter AI through guided tasks that require them to explain, test, compare, document, and reflect on AI-assisted processes, thereby transforming use into informed capability rather than routine dependence. The educational value lies in helping learners recognise when AI can extend reasoning and when independent analysis, domain expertise, or human consultation remains necessary for a defensible academic decision.

Despite growing institutional attention, AI adoption is progressing faster than the development of mature student judgement. Large language models can produce confident responses that contain fabricated information, hidden assumptions, biased patterns, or incomplete reasoning, creating a risk that polished language will be mistaken for trustworthy evidence. Kasneci et al. (2023) describe substantial educational opportunities alongside risks involving misinformation, bias, privacy, and overreliance. Tlili et al. (2023) similarly demonstrate that enthusiasm for conversational AI must be balanced against concerns surrounding responsible educational use. The problem is intensified by unequal prior knowledge, disciplinary differences, and inconsistent guidance across courses. Students may receive strict prohibitions in one subject and active encouragement in another, without a coherent explanation of the principles that should govern responsible use. Ethical capability is equally uneven. Work on technology and ethics indicates that technological transformation requires explicit accountability rather than assuming responsible behaviour will emerge automatically (Yusof & Abd Wahab, 2021). This unresolved combination of technical uncertainty, uneven readiness, and fragmented governance creates the central educational problem addressed here: higher education needs a coherent conception of AI literacy that supports productive use while protecting critical thinking, academic integrity, evidence quality, and student responsibility. This perspective also matters because students encounter AI in different disciplines, assessment cultures, languages, and levels of prior digital experience, so uniform assumptions about readiness can conceal important inequalities.

This conceptual review develops an integrated interpretation of AI literacy as an emerging competency within twenty-first-century higher education. The analysis examines five foundations of competence: conceptual understanding, applied interaction, critical evaluation, ethical judgement, and adaptive learning. It then identifies barriers that can prevent these capabilities from developing consistently, including unequal readiness, overreliance, integrity tensions, algorithmic risk, and fragmented institutional preparation. The argument subsequently explains the mechanisms through which AI literacy can strengthen student capability and translates those mechanisms into implementable pathways for universities. This perspective is necessary because AI literacy is not simply a technology topic; it concerns how students learn, judge evidence, communicate authorship, protect data, solve problems, and prepare for changing professional environments. Employability

research already places value on market readiness and transferable capability (Ghani et al., 2025), while digital transformation scholarship demonstrates that sustainable outcomes require both technical adoption and organisational capability (Yusof, Kamarudin, Wahid, et al., 2025). The intended contribution is therefore a higher education framework that connects individual competence with curriculum, assessment, ethics, and institutional support, providing a coherent basis for developing students who can work with AI critically, responsibly, and independently. Such capability is increasingly relevant to employability because graduates are likely to work in environments where human judgement and automated systems operate together rather than as separate forms of work.

## **2.0 FOUNDATIONS SHAPING AI LITERACY WITHIN CONTEMPORARY HIGHER EDUCATION**

A credible approach to AI literacy must connect technical understanding with educational judgement. Students need sufficient knowledge of artificial intelligence to interpret what systems are doing, practical competence to interact with them purposefully, critical capability to evaluate generated outputs, ethical reasoning to recognise responsibilities, and adaptive learning habits that remain useful as tools evolve. Treating these capabilities separately can produce partial competence, such as effective prompting without verification or ethical awareness without practical application. The five dimensions developed below therefore operate as a connected competency architecture. Together they establish AI literacy as the capacity to understand, use, question, govern, and learn with artificial intelligence in ways that preserve intellectual responsibility. This integrated foundation provides the basis for analysing why student readiness remains uneven and why higher education needs more systematic development of AI capability.

### **2.1 Understanding Core Artificial Intelligence Concepts Within Higher Education**

Conceptual knowledge becomes educationally valuable when students can distinguish model capability from human understanding and translate that distinction into reasoned academic behaviour. The central concern is misconceptions about prediction, training data, and generated confidence. Foundational AI literacy research shows that competence must extend beyond operating a system to include understanding, evaluation, and informed judgement (Yusof, Othman, Zaini, et al., 2025). In practical terms, students need opportunities to connect abstract principles with academic tasks so that distinguishing model capability from human understanding becomes visible in decisions about evidence, reasoning, and responsibility. This is important because intelligent systems can reduce the effort required to generate an answer while increasing the intellectual effort required to determine whether that answer should be trusted. Evidence from digital capability and learning research also suggests that technology produces stronger outcomes when users possess complementary skills and reflective routines rather than treating adoption as an end in itself (Yusof, Razak, Jamaludin, et al., 2025). Accordingly, conceptual knowledge should be developed through guided explanation, practice, comparison, and reflection. Students should be able to articulate why an AI response may be useful, what information is missing, which assumptions require checking, and what part of the final judgement remains their responsibility. The deeper educational implication is calibrated expectations and more defensible academic decisions. This positions AI literacy as a form of intellectual capability that supports learning across disciplines while maintaining the distinction between technological assistance and accountable human judgement.

Frequent AI use does not demonstrate conceptual competence because distinguishing model capability from human understanding require deliberate judgement. The central concern is misconceptions about prediction, training data, and generated confidence. Foundational AI literacy research shows that competence must extend beyond operating a system to include understanding, evaluation, and informed judgement (Yusof, Razak, & Fauzi, 2025). In practical terms, students need opportunities to connect abstract principles with academic tasks so that distinguishing model capability from human understanding becomes visible in decisions about evidence, reasoning, and responsibility. This is important because intelligent systems can reduce the effort required to generate an answer while increasing the intellectual effort required to determine whether that answer should be trusted. Evidence from digital capability and learning research also suggests that technology produces stronger outcomes when users possess complementary skills and reflective routines rather than treating adoption as an end in itself (Yusof, Salleh, & Zahari, 2020). Accordingly, conceptual knowledge should be developed through guided explanation, practice, comparison, and reflection. Students should be able to articulate why an AI response may be useful, what information is missing, which assumptions require checking, and what part of the final judgement remains their responsibility. The deeper educational implication is calibrated expectations and more defensible academic decisions. This positions AI literacy as a form of intellectual capability that supports learning across disciplines while maintaining the distinction between technological assistance and accountable human judgement.

## **2.2 Developing Effective Prompt Engineering Skills Through Academic Practice**

Frequent AI use does not demonstrate applied competence because purposeful prompting and iterative refinement require deliberate judgement. The central concern is surface-level prompting that pursues answers without specifying purpose or constraints. Foundational AI literacy research shows that competence must extend beyond operating a system to include understanding, evaluation, and informed judgement (Zaini et al., 2026). In practical terms, students need opportunities to connect abstract principles with academic tasks so that formulating purposeful instructions and iteratively refining AI-assisted work becomes visible in decisions about evidence, reasoning, and responsibility. This is important because intelligent systems can reduce the effort required to generate an answer while increasing the intellectual effort required to determine whether that answer should be trusted. Evidence from digital capability and learning research also suggests that technology produces stronger outcomes when users possess complementary skills and reflective routines rather than treating adoption as an end in itself (Asio, 2024). Accordingly, applied interaction should be developed through guided explanation, practice, comparison, and reflection. Students should be able to articulate why an AI response may be useful, what information is missing, which assumptions require checking, and what part of the final judgement remains their responsibility. The deeper educational implication is productive human-AI collaboration that keeps students cognitively engaged. This positions AI literacy as a form of intellectual capability that supports learning across disciplines while maintaining the distinction between technological assistance and accountable human judgement.

Applied interaction should be understood as an educational capability that involves purposeful instructions, iterative refinement, and reflective control over AI-assisted work. The central concern is surface-level prompting that pursues answers without specifying purpose or constraints. Foundational AI literacy research shows that competence must extend beyond operating a system to

include understanding, evaluation, and informed judgement (Chen et al., 2025). In practical terms, students need opportunities to connect abstract principles with academic tasks so that formulating purposeful instructions and iteratively refining AI-assisted work becomes visible in decisions about evidence, reasoning, and responsibility. This is important because intelligent systems can reduce the effort required to generate an answer while increasing the intellectual effort required to determine whether that answer should be trusted. Evidence from digital capability and learning research also suggests that technology produces stronger outcomes when users possess complementary skills and reflective routines rather than treating adoption as an end in itself (Hornberger et al., 2023). Accordingly, applied interaction should be developed through guided explanation, practice, comparison, and reflection. Students should be able to articulate why an AI response may be useful, what information is missing, which assumptions require checking, and what part of the final judgement remains their responsibility. The deeper educational implication is productive human-AI collaboration that keeps students cognitively engaged. This positions AI literacy as a form of intellectual capability that supports learning across disciplines while maintaining a clear distinction between technological assistance and accountable human judgement.

### **2.3 Evaluating AI Generated Outputs Through Critical Academic Judgement**

Critical evaluation is an educational capability that requires students to test claims, sources, calculations, assumptions, and logical consistency before accepting AI-generated outputs. The central concern is fluent but inaccurate or fabricated outputs that are accepted without verification. Foundational AI literacy research shows that competence must extend beyond operating a system to include understanding, evaluation, and informed judgement (Kajiwara & Kawabata, 2024). In practical terms, students need opportunities to connect abstract principles with academic tasks so that testing claims, sources, calculations, assumptions, and logical consistency becomes visible in decisions about evidence, reasoning, and responsibility. This is important because intelligent systems can reduce the effort required to generate an answer while increasing the intellectual effort required to determine whether that answer should be trusted. Evidence from digital capability and learning research also suggests that technology produces stronger outcomes when users possess complementary skills and reflective routines rather than treating adoption as an end in itself (Kasneci et al., 2023). Accordingly, critical evaluation should be developed through guided explanation, practice, comparison, and reflection. Students should be able to articulate why an AI response may be useful, what information is missing, which assumptions require checking, and what part of the final judgement remains their responsibility. The deeper educational implication is stronger evidence quality and protection against automated misinformation. This positions AI literacy as a form of intellectual capability that supports learning across disciplines while maintaining a clear distinction between technological assistance and accountable human judgement.

Critical evaluation becomes especially important when university students make academic decisions under technological uncertainty. The central concern is fluent but inaccurate or fabricated outputs that are accepted without verification. Foundational AI literacy research shows that competence must extend beyond operating a system to include understanding, evaluation, and informed judgement (Laupichler et al., 2022). In practical terms, students need opportunities to connect abstract principles with academic tasks so that testing claims, sources, calculations, assumptions, and logical consistency becomes visible in decisions about evidence, reasoning, and responsibility. This is important because intelligent systems can reduce the effort required to generate an answer while

increasing the intellectual effort required to determine whether that answer should be trusted. Evidence from digital capability and learning research also suggests that technology produces stronger outcomes when users possess complementary skills and reflective routines rather than treating adoption as an end in itself (Long & Magerko, 2020). Accordingly, critical evaluation should be developed through guided explanation, practice, comparison, and reflection. Students should be able to articulate why an AI response may be useful, what information is missing, which assumptions require checking, and what part of the final judgement remains their responsibility. The deeper educational implication is stronger evidence quality and protection against automated misinformation. This positions AI literacy as a form of intellectual capability that supports learning across disciplines while maintaining the distinction between technological assistance and accountable human judgement.

## 2.4 Building Ethical Judgement Through Responsible Artificial Intelligence Use

Ethical judgement becomes especially important when university students make decisions involving uncertain boundaries of acceptable AI use. The central concern is unclear boundaries between legitimate assistance and substitution of student work. Foundational AI literacy research shows that competence must extend beyond operating a system to include understanding, evaluation, and informed judgement (Mansoor et al., 2024). In practical terms, students need opportunities to connect abstract principles with academic tasks so that recognising authorship, disclosure, privacy, fairness, and accountability obligations becomes visible in decisions about evidence, reasoning, and responsibility. This is important because intelligent systems can reduce the effort required to generate an answer while increasing the intellectual effort required to determine whether that answer should be trusted. Evidence from digital capability and learning research also suggests that technology produces stronger outcomes when users possess complementary skills and reflective routines rather than treating adoption as an end in itself (Ng et al., 2021). Accordingly, ethical judgement should be developed through guided explanation, practice, comparison, and reflection. Students should be able to articulate why an AI response may be useful, what information is missing, which assumptions require checking, and what part of the final judgement remains their responsibility. The deeper educational implication is responsible participation that preserves academic integrity and social trust. This positions AI literacy as a form of intellectual capability that supports learning across disciplines while maintaining the distinction between technological assistance and accountable human judgement.

Ethical judgement is strategically important because it connects technological participation with accountable learning. The central concern is unclear boundaries between legitimate assistance and substitution of student work. Foundational AI literacy research shows that competence must extend beyond operating a system to include understanding, evaluation, and informed judgement (Tlili et al., 2023). In practical terms, students need opportunities to connect abstract principles with academic tasks so that recognising authorship, disclosure, privacy, fairness, and accountability obligations becomes visible in decisions about evidence, reasoning, and responsibility. This is important because intelligent systems can reduce the effort required to generate an answer while increasing the intellectual effort required to determine whether that answer should be trusted. Evidence from digital capability and learning research also suggests that technology produces stronger outcomes when users possess complementary skills and reflective routines rather than treating adoption as an end in itself (Tzirides et al., 2024). Accordingly, ethical judgement should be

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## **2.5 Developing Future Ready AI Competencies Among University Students**

Adaptive competence is strategically important because it enables students to remain capable as AI technologies, interfaces, and expectations change. The central concern is tool-specific skill that becomes obsolete when interfaces and capabilities change. Foundational AI literacy research shows that competence must extend beyond operating a system to include understanding, evaluation, and informed judgement (Zawacki-Richter et al., 2019). In practical terms, students need opportunities to connect abstract principles with academic tasks so that learning how to learn with rapidly changing AI systems becomes visible in decisions about evidence, reasoning, and responsibility. This is important because intelligent systems can reduce the effort required to generate an answer while increasing the intellectual effort required to determine whether that answer should be trusted. Evidence from digital capability and learning research also suggests that technology produces stronger outcomes when users possess complementary skills and reflective routines rather than treating adoption as an end in itself (Zhao et al., 2024). Accordingly, adaptive competence should be developed through guided explanation, practice, comparison, and reflection. Students should be able to articulate why an AI response may be useful, what information is missing, which assumptions require checking, and what part of the final judgement remains their responsibility. The deeper educational implication is future-ready capability based on transferable principles and reflective learning. This positions AI literacy as a form of intellectual capability that supports learning across disciplines while maintaining the distinction between technological assistance and accountable human judgement.

Adaptive competence becomes educationally valuable when students can learn effectively with rapidly changing AI systems while maintaining reasoned academic behaviour. The central concern is tool-specific skill that becomes obsolete when interfaces and capabilities change. Foundational AI literacy research shows that competence must extend beyond operating a system to include understanding, evaluation, and informed judgement (Gander & Harris, 2024). In practical terms, students need opportunities to connect abstract principles with academic tasks so that learning how to learn with rapidly changing AI systems becomes visible in decisions about evidence, reasoning, and responsibility. This is important because intelligent systems can reduce the effort required to generate an answer while increasing the intellectual effort required to determine whether that answer should be trusted. Evidence from digital capability and learning research also suggests that technology produces stronger outcomes when users possess complementary skills and reflective routines rather than treating adoption as an end in itself (Kelly et al., 2023). Accordingly, adaptive competence should be developed through guided explanation, practice, comparison, and reflection. Students should be able to articulate why an AI response may be useful, what information is missing, which assumptions require checking, and what part of the final judgement remains their responsibility. The deeper educational implication is future-ready capability based on transferable

principles and reflective learning. This positions AI literacy as a form of intellectual capability that supports learning across disciplines while maintaining a clear distinction between technological assistance and accountable human judgement.

### **3.0 PRESSURES LIMITING EQUITABLE RESPONSIBLE AI LITERACY DEVELOPMENT**

The expansion of generative AI does not guarantee equitable or responsible competence among students. Rapid availability can magnify differences in prior knowledge, encourage dependence on fluent automated outputs, create uncertainty about authorship and assessment, expose learners to bias and privacy risks, and reveal inconsistencies in institutional guidance. These pressures are interconnected because weak conceptual knowledge makes verification harder, unclear ethical expectations increase integrity uncertainty, and fragmented curricula leave students without stable principles for decision making. The five challenges examined below represent structural barriers to AI literacy rather than isolated student weaknesses. Their significance lies in the possibility that universities may normalise AI use faster than they develop the judgement needed to govern it. Understanding these pressures is therefore necessary for explaining how AI literacy can be converted from an aspirational idea into a reliable educational capability.

#### **3.1 Unequal Digital Readiness Across Diverse Student Learning Environments**

Uneven readiness becomes educationally significant because differences in technical background, access, language, confidence, and prior experience shape how students engage with AI. The challenge becomes visible through assuming all students begin with comparable knowledge and digital resources, which can prevent students from converting access to AI into reliable academic capability. Rapid adoption often masks differences in prior experience and encourages institutions to focus on immediate tool use instead of the conditions required for responsible learning. Research with university students shows meaningful variation in AI knowledge, confidence, and literacy, indicating that exposure alone does not produce a common competency baseline (Kong et al., 2024). These differences become more consequential when assessment demands, disciplinary conventions, or language practices require students to judge outputs rather than merely obtain them. The same concern appears in wider technology research, where digital participation and adoption create uneven benefits when capability, support, and governance are distributed inconsistently (Southworth et al., 2023). As a result, students who already possess stronger digital or disciplinary knowledge may use AI to extend learning, whereas less prepared students may become more dependent on unverified outputs. The organisational consequence is not only unequal performance but unequal capacity to recognise risk. Unless universities address the underlying conditions, uneven readiness can normalise the false assumption that all students begin with comparable knowledge and digital resources, thereby widening inequality in who can benefit from AI-enhanced learning.

Frequency of AI use cannot conceal uneven readiness because differences in technical background, access, language, confidence, and prior experience require differentiated educational support. The challenge becomes visible through assuming all students begin with comparable knowledge and digital resources, which can prevent students from converting access to AI into reliable academic capability. Rapid adoption often masks differences in prior experience and encourages institutions to focus on immediate tool use instead of the conditions required for responsible learning. Research with university students shows meaningful variation in AI knowledge, confidence, and literacy,

indicating that exposure alone does not produce a common competency baseline (Yusnizahri et al., 2025). These differences become more consequential when assessment demands, disciplinary conventions, or language practices require students to judge outputs rather than merely obtain them. The same concern appears in wider technology research, where digital participation and adoption create uneven benefits when capability, support, and governance are distributed inconsistently (Abd Wahab & Yusof, 2020). As a result, students who already possess stronger digital or disciplinary knowledge may use AI to extend learning, whereas less prepared students may become more dependent on unverified outputs. The organisational consequence is not only unequal performance but unequal capacity to recognise risk. Unless universities address the underlying conditions, uneven readiness can normalise the false assumption that all students begin with comparable knowledge and digital resources, thereby widening inequality in who can benefit from AI-enhanced learning.

### 3.2 Cognitive Overreliance Weakening Independent Student Learning Capabilities

High levels of AI use may conceal cognitive overreliance when students treat automated outputs as substitutes for thinking rather than as provisional resources requiring judgement. The challenge becomes visible through speed and fluency that reduce incentives to question or independently reason, which can prevent students from converting access to AI into reliable academic capability. Rapid adoption often masks differences in prior experience and encourages institutions to focus on immediate tool use instead of the conditions required for responsible learning. Research with university students shows meaningful variation in AI knowledge, confidence, and literacy, indicating that exposure alone does not produce a common competency baseline (Ghani et al., 2025). These differences become more consequential when assessment demands, disciplinary conventions, or language practices require students to judge outputs rather than merely obtain them. The same concern appears in wider technology research, where digital participation and adoption create uneven benefits when capability, support, and governance are distributed inconsistently (Kamarudin et al., 2025). As a result, students who already possess stronger digital or disciplinary knowledge may use AI to extend learning, whereas less prepared students may become more dependent on unverified outputs. The organisational consequence is not only unequal performance but unequal capacity to recognise risk. Unless universities address the underlying conditions, excessive reliance on AI may normalise speed and fluency at the expense of critical questioning and independent reasoning. This can weaken verification practices, encourage shallow learning, and reduce students' engagement with deeper intellectual processes.

Cognitive overreliance must be examined as a learning problem that emerges when automated outputs replace independent reasoning instead of supporting it. The challenge becomes visible through speed and fluency that reduce incentives to question or independently reason, which can prevent students from converting access to AI into reliable academic capability. Rapid adoption often masks differences in prior experience and encourages institutions to focus on immediate tool use instead of the conditions required for responsible learning. Research with university students shows meaningful variation in AI knowledge, confidence, and literacy, indicating that exposure alone does not produce a common competency baseline (Yusof & Abd Wahab, 2021). These differences become more consequential when assessment demands, disciplinary conventions, or language practices require students to judge outputs rather than merely obtain them. The same concern appears in wider technology research, where digital participation and adoption create uneven benefits when capability, support, and governance are distributed inconsistently (Yusof,

2025a). As a result, students who already possess stronger digital or disciplinary knowledge may use AI to extend learning, whereas less prepared students may become more dependent on unverified outputs. The organisational consequence is not only unequal performance but unequal capacity to recognise risk. Unless universities address these conditions, cognitive overreliance may normalise speed and fluency at the expense of verification, deep learning, and independent reasoning.

### **3.3 Academic Integrity Challenges Within AI Supported Student Learning**

Academic integrity becomes difficult to protect when students face uncertain rules concerning acceptable assistance, attribution, authorship, and disclosure. The challenge becomes visible through inconsistent expectations across courses and assessment tasks, which can prevent students from converting access to AI into reliable academic capability. Rapid adoption often masks differences in prior experience and encourages institutions to focus on immediate tool use instead of the conditions required for responsible learning. Research with university students shows meaningful variation in AI knowledge, confidence, and literacy, indicating that exposure alone does not produce a common competency baseline (Yusof, 2025b). These differences become more consequential when assessment demands, disciplinary conventions, or language practices require students to judge outputs rather than merely obtain them. The same concern appears in wider technology research, where digital participation and adoption create uneven benefits when capability, support, and governance are distributed inconsistently (Yusof, 2026). As a result, students who already possess stronger digital or disciplinary knowledge may use AI to extend learning, whereas less prepared students may become more dependent on unverified outputs. The organisational consequence is not only unequal performance but unequal capacity to recognise risk. Unless universities address these conditions, ethical ambiguity may normalise inconsistent expectations across courses, increasing anxiety, accidental misconduct, and uneven academic standards.

Ethical ambiguity becomes consequential when students must make academic decisions without clear expectations about acceptable AI assistance. The challenge becomes visible through inconsistent expectations across courses and assessment tasks, which can prevent students from converting access to AI into reliable academic capability. Rapid adoption often masks differences in prior experience and encourages institutions to focus on immediate tool use instead of the conditions required for responsible learning. Research with university students shows meaningful variation in AI knowledge, confidence, and literacy, indicating that exposure alone does not produce a common competency baseline (Yusof, Abdul Razak, Mat Zin, et al., 2025). These differences become more consequential when assessment demands, disciplinary conventions, or language practices require students to judge outputs rather than merely obtain them. The same concern appears in wider technology research, where digital participation and adoption create uneven benefits when capability, support, and governance are distributed inconsistently (Yusof, Abdul Razak, Misnan, et al., 2026). As a result, students who already possess stronger digital or disciplinary knowledge may use AI to extend learning, whereas less prepared students may become more dependent on unverified outputs. The organisational consequence is not only unequal performance but unequal capacity to recognise risk. Unless universities address the underlying conditions, ethical ambiguity can normalise inconsistent expectations across courses and assessment tasks and generate anxiety, accidental misconduct, and inconsistent academic standards. The problem therefore requires coordinated educational design rather than isolated rules, inconsistent restrictions, or assumptions that students will interpret acceptable AI use in the same way.

### **3.4 Algorithmic Bias Risks Affecting Responsible Student Decision Making**

Algorithmic risk becomes consequential when students rely on AI outputs without sufficient awareness of bias, data limitations, or hidden assumptions. The challenge becomes visible through limited student awareness of how AI systems reproduce social and informational patterns, which can prevent students from converting access to AI into reliable academic capability. Rapid adoption often masks differences in prior experience and encourages institutions to focus on immediate tool use instead of the conditions required for responsible learning. Research with university students shows meaningful variation in AI knowledge, confidence, and literacy, indicating that exposure alone does not produce a common competency baseline (Yusof, Kamarudin, Wahid, et al., 2025). These differences become more consequential when assessment demands, disciplinary conventions, or language practices require students to judge outputs rather than merely obtain them. The same concern appears in wider technology research, where digital participation and adoption create uneven benefits when capability, support, and governance are distributed inconsistently (Yusof, Othman, Zaini, et al., 2025). As a result, students who already possess stronger digital or disciplinary knowledge may use AI to extend learning, whereas less prepared students may become more dependent on unverified outputs. The organisational consequence is not only unequal performance but unequal capacity to recognise risk. Unless universities address the underlying conditions, algorithmic risk can normalise limited student awareness of how AI systems reproduce social and informational patterns and encourage decisions that appear objective while embedding hidden errors or biased assumptions.

Understanding algorithmic risk is strategically important because responsible AI use depends on recognising how automated outputs can reproduce error, bias, or misleading certainty. The challenge becomes visible through limited student awareness of how AI systems reproduce social and informational patterns, which can prevent students from converting access to AI into reliable academic capability. Rapid adoption often masks differences in prior experience and encourages institutions to focus on immediate tool use instead of the conditions required for responsible learning. Research with university students shows meaningful variation in AI knowledge, confidence, and literacy, indicating that exposure alone does not produce a common competency baseline (Yusof, Razak, Jamaludin, et al., 2025). These differences become more consequential when assessment demands, disciplinary conventions, or language practices require students to judge outputs rather than merely obtain them. The same concern appears in wider technology research, where digital participation and adoption create uneven benefits when capability, support, and governance are distributed inconsistently (Yusof, Razak, & Fauzi, 2025). As a result, students who already possess stronger digital or disciplinary knowledge may use AI to extend learning, whereas less prepared students may become more dependent on unverified outputs. The organisational consequence is not only unequal performance but unequal capacity to recognise risk. Unless universities address the underlying conditions, algorithmic risk can normalise limited student awareness of how AI systems reproduce social and informational patterns and encourage decisions that appear objective while embedding hidden errors or biased assumptions.

### **3.5 Institutional Readiness Gaps Constraining Effective AI Literacy Development**

Institutional fragmentation becomes a strategic concern when policies, teaching practices, assessment expectations, and support structures develop without sufficient coordination. The challenge becomes visible through isolated responses that focus on prohibition or tool

demonstrations without competency development, which can prevent students from converting access to AI into reliable academic capability. Rapid adoption often masks differences in prior experience and encourages institutions to focus on immediate tool use instead of the conditions required for responsible learning. Research with university students shows meaningful variation in AI knowledge, confidence, and literacy, indicating that exposure alone does not produce a common competency baseline (Yusof, Salleh, & Zahari, 2020). These differences become more consequential when assessment demands, disciplinary conventions, or language practices require students to judge outputs rather than merely obtain them. The same concern appears in wider technology research, where digital participation and adoption create uneven benefits when capability, support, and governance are distributed inconsistently (Zaini et al., 2026). As a result, students who already possess stronger digital or disciplinary knowledge may use AI to extend learning, whereas less prepared students may become more dependent on unverified outputs. The organisational consequence is not only unequal performance but unequal capacity to recognise risk. Unless universities address the underlying conditions, institutional fragmentation can normalise isolated responses that focus on prohibition or tool demonstrations without competency development and produce inconsistent student experiences alongside weak institutional learning. The problem therefore requires coordinated institutional action that connects policy, curriculum, assessment, staff development, student support, and continuous review.

Institutional fragmentation affects educational quality when uneven policies, staff readiness, curriculum coverage, and support structures create inconsistent expectations for students. The challenge becomes visible through isolated responses that focus on prohibition or tool demonstrations without competency development, which can prevent students from converting access to AI into reliable academic capability. Rapid adoption often masks differences in prior experience and encourages institutions to focus on immediate tool use instead of the conditions required for responsible learning. Research with university students shows meaningful variation in AI knowledge, confidence, and literacy, indicating that exposure alone does not produce a common competency baseline (Asio, 2024). These differences become more consequential when assessment demands, disciplinary conventions, or language practices require students to judge outputs rather than merely obtain them. The same concern appears in wider technology research, where digital participation and adoption create uneven benefits when capability, support, and governance are distributed inconsistently (Chen et al., 2025). As a result, students who already possess stronger digital or disciplinary knowledge may use AI to extend learning, whereas less prepared students may become more dependent on unverified outputs. The organisational consequence is not only unequal performance but unequal capacity to recognise risk. Without stronger coordination, institutional fragmentation can produce inconsistent student experiences, weak staff confidence, and limited organisational learning about responsible AI education.

#### **4.0 MECHANISMS CONNECTING AI LITERACY WITH STUDENT CAPABILITY DEVELOPMENT**

AI literacy strengthens student capability through identifiable learning mechanisms rather than through simple exposure to intelligent tools. Conceptual knowledge calibrates expectations, purposeful interaction turns AI into a learning partner rather than an answer machine, verification protects evidence quality, ethical reasoning guides legitimate participation, and institutional support creates conditions in which these behaviours can become routine. The analytical task is therefore to

explain how these mechanisms convert knowledge and practice into dependable academic judgement. Their value is especially visible when students face ambiguous outputs, unfamiliar tasks, or competing expectations about appropriate AI use. The five mechanisms developed below interpret the challenges previously identified and clarify why students with similar access to AI may achieve very different educational outcomes. This explanation provides the bridge between diagnosing weak AI literacy and designing higher education practices capable of strengthening it.

#### 4.1 Conceptual Knowledge Supporting Informed Student Engagement With AI

Conceptual knowledge becomes useful when students understand probabilistic generation, training constraints, and model limitations well enough to guide academic decisions. The mechanism operates because understanding probabilistic generation, training constraints, and model limitations changes how students interpret and respond to AI-generated information. Instead of treating AI as an autonomous source of authority, literate learners use it within a wider process that includes disciplinary knowledge, evidence, reflection, and human accountability. AI literacy scholarship supports this interpretation by showing that understanding and evaluation are mutually reinforcing capabilities rather than separate stages of tool use (Hornberger et al., 2023). When students know why a system may generate uncertainty, they are more likely to question confidence, compare alternatives, and recognise the limits of automation. Research on technology-enabled learning similarly indicates that purposeful interaction and structured reflection can strengthen capability when students remain active participants in the learning process (Kajiwara & Kawabata, 2024). This explains why equal access to an AI platform can produce unequal educational outcomes: the decisive difference lies in the quality of the reasoning surrounding the interaction. Conceptual knowledge therefore acts as a conversion mechanism that transforms technological availability into better calibration of reliance and independent judgement. Its strategic significance extends to future professional contexts, where graduates will increasingly need to combine automated assistance with evidence-based judgement, communicate uncertainty, and remain responsible for decisions that cannot be delegated to a model.

Frequent AI use cannot substitute for conceptual competence because understanding probabilistic generation, training constraints, and model limitations require deliberate judgement. The mechanism operates because understanding probabilistic generation, training constraints, and model limitations changes how students interpret and respond to AI-generated information. Instead of treating AI as an autonomous source of authority, literate learners use it within a wider process that includes disciplinary knowledge, evidence, reflection, and human accountability. AI literacy scholarship supports this interpretation by showing that understanding and evaluation are mutually reinforcing capabilities rather than separate stages of tool use (Kasneci et al., 2023). When students know why a system may generate uncertainty, they are more likely to question confidence, compare alternatives, and recognise the limits of automation. Research on technology-enabled learning similarly indicates that purposeful interaction and structured reflection can strengthen capability when students remain active participants in the learning process (Laupichler et al., 2022). This explains why equal access to an AI platform can produce unequal educational outcomes: the decisive difference lies in the quality of the reasoning surrounding the interaction. Conceptual knowledge therefore acts as a conversion mechanism that transforms technological availability into better calibration of reliance and independent judgement. Its strategic significance extends to future professional contexts, where graduates will increasingly need to combine automated assistance with

evidence-based judgement, communicate uncertainty, and remain responsible for decisions that cannot be delegated to a model.

#### **4.2 Human AI Collaboration Strengthening Higher Order Learning Capabilities**

Effective human-AI interaction cannot be measured by usage frequency because productive dialogue, iteration, comparison, and reflection depend on deliberate judgement. The mechanism operates because using dialogue, iteration, comparison, and reflection to extend learning changes how students interpret and respond to AI-generated information. Instead of treating AI as an autonomous source of authority, literate learners use it within a wider process that includes disciplinary knowledge, evidence, reflection, and human accountability. AI literacy scholarship supports this interpretation by showing that understanding and evaluation are mutually reinforcing capabilities rather than separate stages of tool use (Long & Magerko, 2020). When students know why a system may generate uncertainty, they are more likely to question confidence, compare alternatives, and recognise the limits of automation. Research on technology-enabled learning similarly indicates that purposeful interaction and structured reflection can strengthen capability when students remain active participants in the learning process (Mansoor et al., 2024). This explains why equal access to an AI platform can produce unequal educational outcomes: the decisive difference lies in the quality of the reasoning surrounding the interaction. Human-ai interaction therefore acts as a conversion mechanism that transforms technological availability into co-productive learning in which AI stimulates rather than replaces thinking. Its strategic significance extends to future professional contexts, where graduates will increasingly need to combine automated assistance with evidence-based judgement, communicate uncertainty, and remain responsible for decisions that cannot be delegated to a model.

Human-AI interaction should be understood as an educational capability in which dialogue, iteration, comparison, and reflection extend rather than replace student reasoning. The mechanism operates because using dialogue, iteration, comparison, and reflection to extend learning changes how students interpret and respond to AI-generated information. Instead of treating AI as an autonomous source of authority, literate learners use it within a wider process that includes disciplinary knowledge, evidence, reflection, and human accountability. AI literacy scholarship supports this interpretation by showing that understanding and evaluation are mutually reinforcing capabilities rather than separate stages of tool use (Ng et al., 2021). When students know why a system may generate uncertainty, they are more likely to question confidence, compare alternatives, and recognise the limits of automation. Research on technology-enabled learning similarly indicates that purposeful interaction and structured reflection can strengthen capability when students remain active participants in the learning process (Tlili et al., 2023). This explains why equal access to an AI platform can produce unequal educational outcomes: the decisive difference lies in the quality of reasoning surrounding each interaction. Human-AI interaction therefore acts as a conversion mechanism that transforms technological availability into co-productive learning in which AI stimulates rather than replaces thinking. Its strategic significance extends to professional contexts, where graduates will increasingly need to combine automated assistance with evidence-based judgement, communicate uncertainty, and remain accountable for decisions requiring human interpretation, ethical consideration, and contextual understanding.

### 4.3 Critical Verification Strengthening Reliability Within AI Supported Learning

Critical verification is an educational capability that requires AI claims to be checked against credible evidence, disciplinary standards, and transparent reasoning. The mechanism operates because cross-checking AI claims with credible evidence and disciplinary standards changes how students interpret and respond to AI-generated information. Instead of treating AI as an autonomous source of authority, literate learners use it within a wider process that includes disciplinary knowledge, evidence, reflection, and human accountability. AI literacy scholarship supports this interpretation by showing that understanding and evaluation are mutually reinforcing capabilities rather than separate stages of tool use (Tzirides et al., 2024). When students know why a system may generate uncertainty, they are more likely to question confidence, compare alternatives, and recognise the limits of automation. Research on technology-enabled learning similarly indicates that purposeful interaction and structured reflection can strengthen capability when students remain active participants in the learning process (Zawacki-Richter et al., 2019). This explains why equal access to an AI platform can produce unequal educational outcomes: the decisive difference lies in the quality of the reasoning surrounding the interaction. Critical verification therefore acts as a conversion mechanism that transforms technological availability into academic work that remains traceable, defensible, and evidence-based. Its strategic significance extends to future professional contexts, where graduates will increasingly need to combine automated assistance with evidence-based judgement, communicate uncertainty, and remain responsible for decisions that cannot be delegated to a model.

Critical verification becomes essential when students make academic decisions using outputs whose accuracy, sources, or assumptions may be uncertain. The mechanism operates because cross-checking AI claims with credible evidence and disciplinary standards changes how students interpret and respond to AI-generated information. Instead of treating AI as an autonomous source of authority, literate learners use it within a wider process that includes disciplinary knowledge, evidence, reflection, and human accountability. AI literacy scholarship supports this interpretation by showing that understanding and evaluation are mutually reinforcing capabilities rather than separate stages of tool use (Zhao et al., 2024). When students know why a system may generate uncertainty, they are more likely to question confidence, compare alternatives, and recognise the limits of automation. Research on technology-enabled learning similarly indicates that purposeful interaction and structured reflection can strengthen capability when students remain active participants in the learning process (Gander & Harris, 2024). This explains why equal access to an AI platform can produce unequal educational outcomes: the decisive difference lies in the quality of the reasoning surrounding the interaction. Critical verification therefore acts as a conversion mechanism that transforms technological availability into academic work that remains traceable, defensible, and evidence-based. Its strategic significance extends to future professional contexts, where graduates will increasingly need to combine automated assistance with evidence-based judgement, communicate uncertainty, and remain responsible for decisions that cannot be delegated to a model.

### 4.4 Ethical Reasoning Shaping Responsible Student Use Of AI

Ethical reasoning becomes essential when students must decide how AI can be used without compromising authorship, fairness, privacy, or academic responsibility. The mechanism operates because linking technical choices to consequences for privacy, fairness, authorship, and

accountability changes how students interpret and respond to AI-generated information. Instead of treating AI as an autonomous source of authority, literate learners use it within a wider process that includes disciplinary knowledge, evidence, reflection, and human accountability. AI literacy scholarship supports this interpretation by showing that understanding and evaluation are mutually reinforcing capabilities rather than separate stages of tool use (Kelly et al., 2023). When students know why a system may generate uncertainty, they are more likely to question confidence, compare alternatives, and recognise the limits of automation. Research on technology-enabled learning similarly indicates that purposeful interaction and structured reflection can strengthen capability when students remain active participants in the learning process (Kong et al., 2024). This explains why equal access to an AI platform can produce unequal educational outcomes: the decisive difference lies in the quality of the reasoning surrounding the interaction. Ethical reasoning therefore acts as a conversion mechanism that transforms technological availability into internalised judgement that transfers across tools and contexts. Its strategic significance extends to future professional contexts, where graduates will increasingly need to combine automated assistance with evidence-based judgement, communicate uncertainty, and remain responsible for decisions that cannot be delegated to a model.

Ethical reasoning is strategically important because it connects technological participation with accountable academic practice. The mechanism operates because linking technical choices to consequences for privacy, fairness, authorship, and accountability changes how students interpret and respond to AI-generated information. Instead of treating AI as an autonomous source of authority, literate learners use it within a wider process that includes disciplinary knowledge, evidence, reflection, and human accountability. AI literacy scholarship supports this interpretation by showing that understanding and evaluation are mutually reinforcing capabilities rather than separate stages of tool use (Southworth et al., 2023). When students know why a system may generate uncertainty, they are more likely to question confidence, compare alternatives, and recognise the limits of automation. Research on technology-enabled learning similarly indicates that purposeful interaction and structured reflection can strengthen capability when students remain active participants in the learning process (Yusnilzahri et al., 2025). This explains why equal access to an AI platform can produce unequal educational outcomes: the decisive difference lies in the quality of the reasoning surrounding the interaction. Ethical reasoning therefore acts as a conversion mechanism that transforms technological availability into internalised judgement that transfers across tools and contexts. Its strategic significance extends to future professional contexts, where graduates will increasingly need to combine automated assistance with evidence-based judgement, communicate uncertainty, and remain responsible for decisions that cannot be delegated to a model.

#### **4.5 Institutional Capability Enabling Sustainable Student AI Literacy Development**

Institutional support is strategically important because students cannot develop reliable AI literacy through individual effort alone. The mechanism operates because aligning policy, teaching, assessment, library expertise, technology access, and staff development changes how students interpret and respond to AI-generated information. Instead of treating AI as an autonomous source of authority, literate learners use it within a wider process that includes disciplinary knowledge, evidence, reflection, and human accountability. AI literacy scholarship supports this interpretation by showing that understanding and evaluation are mutually reinforcing capabilities rather than separate stages of tool use (Abd Wahab & Yusof, 2020). When students know why a system may

generate uncertainty, they are more likely to question confidence, compare alternatives, and recognise the limits of automation. Research on technology-enabled learning similarly indicates that purposeful interaction and structured reflection can strengthen capability when students remain active participants in the learning process (Ghani et al., 2025). This explains why equal access to an AI platform can produce unequal educational outcomes: the decisive difference lies in the quality of the reasoning surrounding the interaction. Institutional support therefore acts as a conversion mechanism that transforms technological availability into shared expectations and sustainable capability across programmes. Its strategic significance extends to future professional contexts, where graduates will increasingly need to combine automated assistance with evidence-based judgement, communicate uncertainty, and remain responsible for decisions that cannot be delegated to a model.

Institutional support becomes educationally valuable when policy, teaching, assessment, library expertise, technology access, and staff development operate coherently. The mechanism operates because aligning policy, teaching, assessment, library expertise, technology access, and staff development changes how students interpret and respond to AI-generated information. Instead of treating AI as an autonomous source of authority, literate learners use it within a wider process that includes disciplinary knowledge, evidence, reflection, and human accountability. AI literacy scholarship supports this interpretation by showing that understanding and evaluation are mutually reinforcing capabilities rather than separate stages of tool use (Kamarudin et al., 2025). When students know why a system may generate uncertainty, they are more likely to question confidence, compare alternatives, and recognise the limits of automation. Research on technology-enabled learning similarly indicates that purposeful interaction and structured reflection can strengthen capability when students remain active participants in the learning process (Yusof & Abd Wahab, 2021). This explains why equal access to an AI platform can produce unequal educational outcomes: the decisive difference lies in the quality of the reasoning surrounding the interaction. Institutional support therefore acts as a conversion mechanism that transforms technological availability into shared expectations and sustainable capability across programmes. Its strategic significance extends to future professional contexts, where graduates will increasingly need to combine automated assistance with evidence-based judgement, communicate uncertainty, and remain responsible for decisions that cannot be delegated to a model.

## **5.0 STRATEGIC PATHWAYS STRENGTHENING STUDENT AI LITERACY DEVELOPMENT**

Universities need clear implementation pathways that embed AI literacy within curriculum, assessment, student support, and everyday academic practice. Effective development cannot depend on optional workshops alone because AI now influences writing, research, coding, problem solving, creativity, and professional preparation across disciplines. Strategic action should therefore embed core competencies throughout programmes, provide experiential and discipline-relevant learning, institutionalise verification practices, integrate ethics and academic integrity, and ensure inclusive access to guidance and support. These pathways translate the analytical mechanisms identified earlier into practical institutional capability. Their purpose is not to promote unrestricted AI use, but to create conditions in which students can make informed decisions about when, why, and how AI should be used. A coherent institutional approach can thereby support innovation while protecting evidence quality, intellectual independence, fairness, and long-term graduate adaptability.

### **5.1 Embedding AI Literacy Across Contemporary Higher Education Curricula**

Curriculum integration becomes effective when AI literacy outcomes are mapped progressively across introductory, intermediate, and advanced learning. An effective institutional response should make mapping AI literacy outcomes across introductory, intermediate, and advanced learning a recurring feature of teaching and assessment rather than an optional activity for students who already have strong digital confidence. The implementation logic begins with clear learning outcomes that identify what students should understand, demonstrate, verify, and justify at different stages of their programme. Evidence on AI literacy development indicates that structured learning experiences are more valuable than passive exposure because students need guided opportunities to practise judgement and receive feedback (Yusof, 2025a). Wider research on digital transformation also shows that sustainable capability depends on systems, leadership, and learning routines that support technology use over time (Yusof, 2025b). Implementation should therefore combine curriculum design, staff development, accessible learning resources, assessment guidance, and opportunities for students to document how AI contributed to their work. This makes competence observable and reduces ambiguity about expectations. The capability required is institutional coherence: policies, teaching practices, and support services must reinforce the same principles even when specific tools change. The expected outcome is progressive competency development that becomes part of graduate capability. Over the longer term, curriculum integration can help universities move beyond reactive debates about individual applications and establish a durable educational approach in which innovation is accompanied by evidence quality, transparency, inclusion, and accountable student learning.

Curriculum integration should not be judged by how often students use AI, but by whether literacy outcomes develop progressively across levels of study. An effective institutional response should make mapping AI literacy outcomes across introductory, intermediate, and advanced learning a recurring feature of teaching and assessment rather than an optional activity for students who already have strong digital confidence. The implementation logic begins with clear learning outcomes that identify what students should understand, demonstrate, verify, and justify at different stages of their programme. Evidence on AI literacy development indicates that structured learning experiences are more valuable than passive exposure because students need guided opportunities to practise judgement and receive feedback (Yusof, 2026). Wider research on digital transformation also shows that sustainable capability depends on systems, leadership, and learning routines that support technology use over time (Yusof, Abdul Razak, Mat Zin, et al., 2025). Implementation should therefore combine curriculum design, staff development, accessible learning resources, assessment guidance, and opportunities for students to document how AI contributed to their work. This makes competence observable and reduces ambiguity about expectations. The capability required is institutional coherence: policies, teaching practices, and support services must reinforce the same principles even when specific tools change. The expected outcome is progressive competency development that becomes part of graduate capability. Over the longer term, curriculum integration can help universities establish progressive competency development as a normal part of graduate capability rather than an optional response to individual AI tools.

### **5.2 Advancing Experiential AI Learning Through Authentic Academic Tasks**

Experiential learning becomes meaningful when students use authentic disciplinary problems, comparison tasks, prompt iteration, and reflective documentation to develop judgement. An effective

institutional response should make using authentic disciplinary problems, comparison tasks, prompt iteration, and reflective documentation a recurring feature of teaching and assessment rather than an optional activity for students who already have strong digital confidence. The implementation logic begins with clear learning outcomes that identify what students should understand, demonstrate, verify, and justify at different stages of their programme. Evidence on AI literacy development indicates that structured learning experiences are more valuable than passive exposure because students need guided opportunities to practise judgement and receive feedback (Yusof, Abdul Razak, Misnan, et al., 2026). Wider research on digital transformation also shows that sustainable capability depends on systems, leadership, and learning routines that support technology use over time (Yusof, Kamarudin, Wahid, et al., 2025). Implementation should therefore combine curriculum design, staff development, accessible learning resources, assessment guidance, and opportunities for students to document how AI contributed to their work. This makes competence observable and reduces ambiguity about expectations. The capability required is institutional coherence: policies, teaching practices, and support services must reinforce the same principles even when specific tools change. The expected outcome is transferable practical competence grounded in authentic academic reasoning. Over the longer term, experiential learning can help universities move beyond tool familiarity and build transferable practical competence grounded in authentic academic reasoning.

Experiential AI learning should be designed around authentic disciplinary problems, comparison tasks, prompt iteration, and reflective documentation rather than passive tool exposure. An effective institutional response should make using authentic disciplinary problems, comparison tasks, prompt iteration, and reflective documentation a recurring feature of teaching and assessment rather than an optional activity for students who already have strong digital confidence. The implementation logic begins with clear learning outcomes that identify what students should understand, demonstrate, verify, and justify at different stages of their programme. Evidence on AI literacy development indicates that structured learning experiences are more valuable than passive exposure because students need guided opportunities to practise judgement and receive feedback (Yusof, Othman, Zaini, et al., 2025). Wider research on digital transformation also shows that sustainable capability depends on systems, leadership, and learning routines that support technology use over time (Yusof, Razak, Jamaludin, et al., 2025). Implementation should therefore combine curriculum design, staff development, accessible learning resources, assessment guidance, and opportunities for students to document how AI contributed to their work. This makes competence observable and reduces ambiguity about expectations. The capability required is institutional coherence: policies, teaching practices, and support services must reinforce the same principles even when specific tools change. The expected outcome is transferable practical competence grounded in authentic academic reasoning. Over the longer term, experiential learning can help universities create durable learning habits that remain valuable as AI systems, interfaces, and disciplinary practices change.

### **5.3 Strengthening Evidence Verification Practices Within AI Supported Learning**

Verification practice becomes a core academic capability when students trace evidence, check sources, compare facts, and explain uncertainty in AI-assisted work. An effective institutional response should make requiring evidence tracing, source checks, fact comparison, and explanation of uncertainty a recurring feature of teaching and assessment rather than an optional activity for students who already have strong digital confidence. The implementation logic begins with clear learning outcomes that identify what students should understand, demonstrate, verify, and justify at

different stages of their programme. Evidence on AI literacy development indicates that structured learning experiences are more valuable than passive exposure because students need guided opportunities to practise judgement and receive feedback (Yusof, Razak, & Fauzi, 2025). Wider research on digital transformation also shows that sustainable capability depends on systems, leadership, and learning routines that support technology use over time (Yusof, Salleh, & Zahari, 2020). Implementation should therefore combine curriculum design, staff development, accessible learning resources, assessment guidance, and opportunities for students to document how AI contributed to their work. This makes competence observable and reduces ambiguity about expectations. The capability required is institutional coherence: policies, teaching practices, and support services must reinforce the same principles even when specific tools change. The expected outcome is routine critical habits that protect quality across AI-assisted tasks. Over the longer term, verification practice can help universities establish routine critical habits that protect evidence quality across AI-assisted academic tasks.

Verification practice becomes consequential when students must decide whether AI-generated claims are sufficiently reliable for academic use. An effective institutional response should make requiring evidence tracing, source checks, fact comparison, and explanation of uncertainty a recurring feature of teaching and assessment rather than an optional activity for students who already have strong digital confidence. The implementation logic begins with clear learning outcomes that identify what students should understand, demonstrate, verify, and justify at different stages of their programme. Evidence on AI literacy development indicates that structured learning experiences are more valuable than passive exposure because students need guided opportunities to practise judgement and receive feedback (Zaini et al., 2026). Wider research on digital transformation also shows that sustainable capability depends on systems, leadership, and learning routines that support technology use over time (Asio, 2024). Implementation should therefore combine curriculum design, staff development, accessible learning resources, assessment guidance, and opportunities for students to document how AI contributed to their work. This makes competence observable and reduces ambiguity about expectations. The capability required is institutional coherence: policies, teaching practices, and support services must reinforce the same principles even when specific tools change. The expected outcome is routine critical habits that protect quality across AI-assisted tasks. Over the longer term, verification practice can help universities move beyond reactive debates about individual applications and establish a durable educational approach in which innovation is accompanied by evidence quality, transparency, inclusion, and accountable student learning.

#### **5.4 Establishing Responsible AI Governance Within Student Academic Practice**

Responsible AI governance becomes consequential when students need consistent expectations about authorship, disclosure, privacy, evidence, and acceptable assistance. An effective institutional response should make embedding disclosure, privacy, bias, attribution, consent, and integrity into teaching and assessment a recurring feature of teaching and assessment rather than an optional activity for students who already have strong digital confidence. The implementation logic begins with clear learning outcomes that identify what students should understand, demonstrate, verify, and justify at different stages of their programme. Evidence on AI literacy development indicates that structured learning experiences are more valuable than passive exposure because students need guided opportunities to practise judgement and receive feedback (Chen et al., 2025). Wider research on digital transformation also shows that sustainable capability depends on systems, leadership, and

learning routines that support technology use over time (Hornberger et al., 2023). Implementation should therefore combine curriculum design, staff development, accessible learning resources, assessment guidance, and opportunities for students to document how AI contributed to their work. This makes competence observable and reduces ambiguity about expectations. The capability required is institutional coherence: policies, teaching practices, and support services must reinforce the same principles even when specific tools change. The expected outcome is responsible AI use based on transparent and explainable choices. Over the longer term, responsible governance can help universities establish clear, consistent expectations while preserving sufficient flexibility for disciplinary differences.

Responsible governance is strategically important because it connects technological participation with accountable academic practice. An effective institutional response should make embedding disclosure, privacy, bias, attribution, consent, and integrity into teaching and assessment a recurring feature of teaching and assessment rather than an optional activity for students who already have strong digital confidence. The implementation logic begins with clear learning outcomes that identify what students should understand, demonstrate, verify, and justify at different stages of their programme. Evidence on AI literacy development indicates that structured learning experiences are more valuable than passive exposure because students need guided opportunities to practise judgement and receive feedback (Kajiwara & Kawabata, 2024). Wider research on digital transformation also shows that sustainable capability depends on systems, leadership, and learning routines that support technology use over time (Kasneci et al., 2023). Implementation should therefore combine curriculum design, staff development, accessible learning resources, assessment guidance, and opportunities for students to document how AI contributed to their work. This makes competence observable and reduces ambiguity about expectations. The capability required is institutional coherence: policies, teaching practices, and support services must reinforce the same principles even when specific tools change. The expected outcome is responsible AI use based on transparent and explainable choices. Over the longer term, responsible governance can connect innovation with transparency, evidence quality, student accountability, and proportionate academic oversight.

### **5.5 Creating Inclusive AI Learning Ecosystems Across Higher Education**

Inclusive institutional ecosystems are strategically important because reliable AI literacy depends on access, capability, support, governance, and continuous learning. An effective institutional response should make combining equitable access, staff capability, student support, governance, and continuous review a recurring feature of teaching and assessment rather than an optional activity for students who already have strong digital confidence. The implementation logic begins with clear learning outcomes that identify what students should understand, demonstrate, verify, and justify at different stages of their programme. Evidence on AI literacy development indicates that structured learning experiences are more valuable than passive exposure because students need guided opportunities to practise judgement and receive feedback (Laupichler et al., 2022). Wider research on digital transformation also shows that sustainable capability depends on systems, leadership, and learning routines that support technology use over time (Long & Magerko, 2020). Implementation should therefore combine curriculum design, staff development, accessible learning resources, assessment guidance, and opportunities for students to document how AI contributed to their work. This makes competence observable and reduces ambiguity about expectations. The capability

required is institutional coherence: policies, teaching practices, and support services must reinforce the same principles even when specific tools change. The expected outcome is inclusive and adaptable AI literacy development across the university. Over the longer term, institutional ecosystems can help universities move beyond reactive debates about individual applications and establish a durable educational approach in which innovation is accompanied by evidence quality, transparency, inclusion, and accountable student learning.

The educational value of institutional ecosystems depends on whether students can translate combining equitable access, staff capability, student support, governance, and continuous review into reasoned academic behaviour. An effective institutional response should make combining equitable access, staff capability, student support, governance, and continuous review a recurring feature of teaching and assessment rather than an optional activity for students who already have strong digital confidence. The implementation logic begins with clear learning outcomes that identify what students should understand, demonstrate, verify, and justify at different stages of their programme. Evidence on AI literacy development indicates that structured learning experiences are more valuable than passive exposure because students need guided opportunities to practise judgement and receive feedback (Mansoor et al., 2024). Wider research on digital transformation also shows that sustainable capability depends on systems, leadership, and learning routines that support technology use over time (Ng et al., 2021). Implementation should therefore combine curriculum design, staff development, accessible learning resources, assessment guidance, and opportunities for students to document how AI contributed to their work. This makes competence observable and reduces ambiguity about expectations. The capability required is institutional coherence: policies, teaching practices, and support services must reinforce the same principles even when specific tools change. The expected outcome is inclusive and adaptable AI literacy development across the university. Over the longer term, inclusive institutional ecosystems can help universities sustain adaptable AI literacy development even as technologies, student needs, and professional expectations continue to change.

## **6.0 CONCLUSION**

AI literacy is becoming a defining competency of higher education because artificial intelligence increasingly mediates how students search, write, analyse, create, and solve problems. The central argument developed here is that competent participation requires considerably more than operational familiarity. Students need conceptual understanding to interpret what AI systems can plausibly do, applied competence to interact with them purposefully, critical evaluation to test outputs against evidence, ethical judgement to recognise responsibility, and adaptive learning capacity to remain effective as technologies change. These dimensions reinforce one another. Practical fluency without verification can produce confident error, while ethical awareness without experience can remain abstract. The academic contribution is therefore an integrated view of AI literacy as a connected capability architecture that preserves human judgement while enabling productive use of intelligent systems. This interpretation also explains why simple access to generative AI cannot be treated as educational progress. What matters is whether students can transform access into reasoned, transparent, and accountable learning decisions.

The analysis also demonstrates that the main barriers to AI literacy are not purely individual. Uneven prior knowledge, dependence on fluent outputs, inconsistent integrity expectations, algorithmic

opacity, privacy concerns, and fragmented institutional guidance shape the conditions under which students learn to use AI. Universities therefore carry a responsibility to design environments in which responsible competence can develop. Curriculum integration, experiential learning, evidence verification, ethical guidance, transparent assessment expectations, staff development, and inclusive access should operate together rather than as disconnected initiatives. Such an approach can reduce the risk that AI widens existing capability gaps or shifts academic responsibility toward opaque technological processes. It can also strengthen graduate readiness by teaching students how to combine technological assistance with disciplinary knowledge, uncertainty management, communication, and independent judgement. The managerial and policy implication is that AI literacy should be treated as an institution-wide educational capability with clear ownership, continuous review, and sufficient flexibility to accommodate disciplinary differences.

The longer-term significance of AI literacy lies in its capacity to help higher education respond to technologies that will continue to change faster than individual tools can be incorporated into formal curricula. Universities cannot prepare students by teaching a fixed interface or a temporary list of permitted applications. They can, however, develop durable principles for understanding automated systems, asking better questions, verifying evidence, explaining decisions, protecting data, recognising bias, disclosing assistance, and retaining responsibility for intellectual work. These principles create a foundation for continued learning as models, professional expectations, and regulatory environments evolve. Future research should strengthen validated measures of AI literacy across disciplines, cultures, and levels of study and should examine how particular pedagogical approaches influence both competence and responsible behaviour over time. For contemporary higher education, the strategic objective is not to produce students who merely use artificial intelligence more frequently, but graduates who can decide when AI adds value, when it introduces unacceptable risk, and how human judgement must govern its contribution to learning and professional practice.

## DECLARATIONS

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### 2. Conflict of Interest

The authors declare that they have no financial, professional, institutional, or personal interests that could have influenced the development, interpretation, or presentation of this article. No circumstances or relationships exist that could reasonably be perceived as affecting the objectivity or academic integrity of the work.

### 3. Author Contribution Statement

Nor Shamila Abdul Karim: Conceptualization, development of the review framework, literature synthesis, interpretation of the literature, preparation of the original manuscript, and critical revision.

Muhamad Ali Imran Kamarudin: Literature synthesis, development of conceptual arguments, interpretation of scholarly evidence, critical review, and manuscript refinement.

Both authors contributed intellectually to the development of the article, critically reviewed the manuscript, and approved the final version for publication.

#### 4. Ethics Statement

This article is a conceptual review based exclusively on published scholarly literature and does not involve human participants, personal or identifiable information, surveys, interviews, experiments, or primary data collection. Accordingly, institutional ethical approval and informed consent were not required. The article was developed in accordance with established principles of academic integrity, responsible scholarship, and appropriate acknowledgement of published sources. The authors remain responsible for the accuracy, interpretation, and scholarly presentation of the literature incorporated into the review.

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