

RESEARCH ARTICLE

Artificial Intelligence and the Transformation of Teaching Practices in Contemporary Higher Education

Muhamad Fitri Radzuan^{1*}, Mohamad Nizam Adhaa Kamarudin², Mohd Noor Afiq Ramlee³¹ Faculty of Education and Social Sciences, University College MAIWP International, Malaysia² Fakulti Komputeran dan Meta-Teknologi, Universiti Pendidikan Sultan Idris, Malaysia³ Universiti Sains Islam Malaysia, Nilai Negeri sembilan, Malaysia**CORRESPONDING AUTHOR**Muhamad Fitri Radzuan
Email: fitri@ucmi.edu.my**ARTICLE HISTORY**

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ABSTRACT

Artificial intelligence is reshaping university teaching by changing how educators design learning activities, generate instructional resources, provide feedback, support inquiry, and evaluate student performance. Its educational value depends on pedagogical judgement rather than technological capability alone. This conceptual study develops a teaching-centred perspective on artificial intelligence in contemporary higher education by integrating scholarship on pedagogical augmentation, adaptive learning, assessment, educator capability, verification, academic integrity, professional learning, and governance. Artificial intelligence can strengthen instructional responsiveness, feedback, curriculum innovation, and student support when educators retain authority over learning purposes, verify generated knowledge, and make student reasoning visible. The same technologies can weaken educational quality when convenience replaces intellectual effort, generated outputs are accepted without scrutiny, assessment no longer provides credible evidence of learning, or institutional expectations remain unclear. Sustainable transformation therefore requires purposeful curriculum integration, authentic assessment, continuous educator development, transparent governance, and explicit verification practices. The central contribution is a coherent conceptual account that positions artificial intelligence as a pedagogical resource whose legitimacy rests on disciplinary judgement, responsible use, human accountability, and demonstrable learning value rather than automation itself.

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1. INTRODUCTION

The growing integration of artificial intelligence into higher education has significantly expanded the technological capabilities available to educators in designing and delivering learning experiences. Generative artificial intelligence has accelerated this development by enabling the rapid production of explanations, examples, assessment materials, feedback, visual representations, coding assistance, and other forms of instructional content. Its increasing accessibility has consequently extended artificial intelligence beyond specialised educational applications into everyday academic practice, where lecturers and students can engage directly with sophisticated generative systems. Earlier research indicated that scholarship on artificial intelligence in higher education concentrated predominantly on technological applications while giving comparatively limited attention to educators and their pedagogical roles (Zawacki-Richter et al., 2019). Recent developments have shifted this emphasis as generative artificial intelligence becomes increasingly connected with curriculum design, teaching strategies, student engagement, assessment, and academic practice. Bower et al. (2024) demonstrate that educators recognise substantial implications for teaching and assessment as these technologies become more capable and accessible. However, technological capability does not independently determine educational value. The quality of artificial intelligence supported teaching depends considerably on how educators align its use with disciplinary knowledge, learning objectives, student needs, assessment expectations, and appropriate academic standards. This places pedagogical judgement at the centre of contemporary artificial intelligence adoption, particularly because efficient content generation can support teaching while simultaneously creating concerns regarding accuracy, reasoning, academic integrity, student dependency, and the preservation of meaningful intellectual engagement.

Artificial intelligence changes teaching most productively when it functions as pedagogical augmentation rather than instructional substitution. Pedagogical augmentation means that computational capability expands the range, speed, or responsiveness of teaching while educators retain responsibility for learning purposes, disciplinary accuracy, ethical boundaries, and the interpretation of student needs. This distinction matters because a system that can generate plausible text does not understand a course in the professional sense required of an educator. It does not carry responsibility for curriculum coherence, student wellbeing, fairness, or the consequences of inaccurate advice. Kasneci et al. (2023) describe substantial opportunities for large language models in education while also emphasising limitations involving reliability, bias, and responsible use. Tili et al. (2023) similarly portray ChatGPT as a technology with both enabling and disruptive possibilities. In practice, educators can use artificial intelligence to vary examples, produce formative questions, compare explanations, support brainstorming, or reduce repetitive preparation, yet each use requires judgement about whether the output serves the intended learning outcome. Human-centred technology principles are therefore highly relevant to higher education. Yusof and Abd Wahab (2021) argue that technological transformation should remain balanced with ethical considerations, a principle that transfers directly to AI-supported teaching. The value of artificial intelligence is consequently determined by the quality of pedagogical orchestration surrounding it, not by the sophistication of the system alone. Pedagogical legitimacy therefore depends on whether computational assistance strengthens the intellectual work that university education is meant to develop.

Recent scholarship suggests that artificial intelligence is already influencing curriculum design, feedback practices, academic support, assessment, and expectations regarding student capability. Qian (2025) identifies a broad range of pedagogical applications across higher education, while Almasri (2024) shows that artificial intelligence can support learning through adaptive assistance, feedback, and technology-mediated instructional strategies. Chiu (2024) argues that generative artificial intelligence requires higher education to reconsider learning outcomes, AI literacy, assessment, interdisciplinarity, and future workforce preparation. These shifts have particular importance because the educational meaning of a task can change once students gain routine access to systems capable of drafting, summarising, translating, coding, and generating arguments. A conventional assignment may no longer reveal the same evidence of understanding that it once did. At the same time, prohibiting artificial intelligence across all learning activities would ignore its growing relevance to professional and social life. University teaching therefore faces a dual responsibility: students must learn disciplinary knowledge and also develop the judgement required to work responsibly with increasingly capable computational systems. Research on digital mobility and university learning likewise indicates that technology use becomes educationally significant when it is embedded within patterns of behaviour, participation, and purpose (Yusof et al., 2025). Artificial intelligence intensifies this relationship because it can participate directly in the production of academic content, making pedagogical design and student agency inseparable from questions of technological use.

The most difficult problems arise where technological capability exceeds the pedagogical and institutional arrangements available to govern it. Generative systems can produce inaccurate statements, fabricated references, hidden bias, and confident simplifications that are difficult for inexperienced students to detect. They can also weaken conventional evidence of authorship when assessment focuses primarily on polished final products. Xia et al. (2024) show that generative artificial intelligence is already reshaping assessment debates around self-regulated learning, responsible learning, and integrity. Bhullar et al. (2024) similarly identify plagiarism, academic integrity, and institutional responses as major themes in higher education research on ChatGPT. These challenges cannot be resolved through detection software or prohibition alone because the underlying issue concerns what universities want students to know, demonstrate, and become capable of doing. Uneven educator capability creates another difficulty. Ren and Wu (2025) report that successful integration depends on teaching competencies as well as the capacity to respond to emerging challenges. Differences in access, workload, disciplinary norms, and professional development can therefore create uneven educational experiences. Digital transformation research outside education also demonstrates that technological adoption produces value only when organisational capabilities develop alongside the technology (Yusof, 2025a; Yusof, 2026). Higher education requires the same alignment between tools, people, curriculum, assessment, governance, and professional responsibility. These tensions make institutional capability and educator judgement central to any sustainable response to artificial intelligence in teaching.

A rigorous conceptual account of artificial intelligence in higher education must place teaching practice, rather than technological novelty, at its centre. The key question is how educators can use artificial intelligence while preserving disciplinary standards, meaningful student effort, credible assessment, intellectual independence, and professional responsibility. A teaching-centred perspective brings several relationships into view simultaneously: augmentation must remain

connected to explicit learning purposes; adaptive support must not remove productive cognitive difficulty; assessment must capture reasoning rather than polished output alone; educator capability must include verification and ethical judgement; and governance must enable innovation without creating ambiguity. Bayaga (2025) links emerging technologies with pedagogical innovation, whereas Ellis et al. (2025) demonstrate that educators experience generative artificial intelligence in qualitatively different ways. Such variation indicates that transformation is neither automatic nor uniform. It depends on professional agency and institutional conditions. Research on hands-on university learning further shows that meaningful participation is strengthened when learners engage actively with tasks rather than merely receive finished answers (Kamarudin et al., 2025). Artificial intelligence should therefore be incorporated in ways that make reasoning more visible, not less. The resulting conceptual position is that sustainable transformation occurs when computational capability is subordinated to educational purpose, supported by educator learning, disciplined by verification, reflected in authentic assessment, and governed through transparent institutional principles. The strongest conceptual position therefore treats artificial intelligence as a governed pedagogical resource rather than an autonomous driver of educational change.

2.0 FOUNDATIONS SHAPING AI ENABLED UNIVERSITY TEACHING PRACTICES

Artificial intelligence becomes educationally meaningful through the interaction of pedagogy, responsiveness, assessment, educator capability, and professional judgement. These foundations are closely connected because changes in one area alter expectations in the others. A teacher who uses generative systems to personalise explanations must still judge whether those explanations are accurate, appropriately challenging, and aligned with disciplinary outcomes. Assessment must then capture what students understand rather than merely what a system can produce on their behalf. Qian (2025) shows that generative artificial intelligence is already being used across varied pedagogical functions, while Bower et al. (2024) demonstrate growing pressure to reconsider teaching and assessment practices. The central educational issue is therefore alignment. Artificial intelligence should expand the educator's capacity to design, respond, and support without displacing the human judgement required to interpret context, values, and evidence of learning. When these foundations are developed together, technological capability can support richer teaching. When they are separated, rapid adoption can produce inconsistent expectations, superficial activity, and weak evidence of learning quality.

2.1 Pedagogical Augmentation Reshaping Contemporary University Teaching Practices

Pedagogical augmentation is strongest when artificial intelligence extends the educator's capacity to design, explain, question, and respond without transferring educational responsibility to the system. A lecturer may use generative tools to create contrasting examples, simplify a difficult explanation, generate formative questions, or anticipate misconceptions, but the value of each output depends on disciplinary judgement. Bower et al. (2024) found strong educator interest in changing teaching practices in response to generative artificial intelligence, while Qian (2025) documents a wide range of pedagogical uses across higher education. These possibilities should not be interpreted as evidence that more automation produces better teaching. Effective augmentation preserves the teacher's authority to determine learning goals, sequence intellectual difficulty, select appropriate evidence, and decide when students need direct explanation rather than automated assistance. It also preserves the relational dimensions of teaching that involve encouragement, challenge, empathy, and responsiveness to classroom dynamics. Generative systems can increase the supply of

instructional material, yet abundance itself can create cognitive noise when examples are poorly selected or explanations are accepted because they are fluent. Pedagogical augmentation therefore requires deliberate curation. The educator remains responsible for deciding what deserves attention, what must be verified, and how AI-generated resources should contribute to the development of disciplinary understanding rather than simply reduce preparation time. Pedagogical augmentation should therefore be judged by whether it deepens understanding while preserving the educator's responsibility for disciplinary quality.

Augmentation also changes the design of student activity because educators can move beyond using artificial intelligence merely as a content generator. Students can be asked to critique generated explanations, compare competing outputs, detect unsupported claims, improve weak prompts, or explain why a machine-produced answer fails disciplinary standards. Such tasks transform artificial intelligence into an object of inquiry and a partner in reflective learning rather than a shortcut around thinking. Kasneci et al. (2023) argue that large language models offer educational opportunities alongside substantial risks, making guided use more defensible than uncritical adoption. Tlili et al. (2023) similarly emphasise the need to understand both benefits and limitations. A human-centred approach is especially important because the educational purpose of an activity should determine the role assigned to technology. Yusof and Abd Wahab (2021) show, in another technology-intensive context, that ethical considerations must remain integrated with technological transformation. In higher education, this means that students should know when AI assistance is pedagogically useful, when independent reasoning is required, and how responsibility for a final academic claim remains human. Augmentation becomes educationally credible when it expands opportunities for explanation, critique, feedback, and experimentation while preserving the intellectual work that allows students to become capable rather than merely efficient. Its educational value becomes durable when students use computational assistance to extend reasoning rather than avoid the effort required for expertise.

2.2 Adaptive Learning Design Expanding Instructional Responsiveness Capabilities

Adaptive learning design uses artificial intelligence to vary support according to differences in prior knowledge, language, confidence, pace, or misunderstanding. Generative systems can produce alternative explanations, additional examples, stepwise hints, practice questions, and different representations of the same concept, giving educators a practical way to respond to diverse learners without preparing every variation manually. Almasri (2024) reports that artificial intelligence can support personalised and adaptive learning, while Qian (2025) identifies personalisation as a recurring pedagogical application in higher education. The educational advantage, however, depends on how adaptation is governed. Effective support should help students progress toward shared disciplinary standards rather than create permanently simplified pathways that lower expectations for those who initially struggle. Educators therefore need to distinguish temporary scaffolding from substitution. A hint that helps a student resume problem solving can strengthen learning; a complete generated solution offered too early can remove the productive difficulty through which expertise develops. Adaptive design also requires attention to the quality of information used to infer learner needs. Students may conceal uncertainty, overestimate understanding, or accept machine-generated feedback without reflection. Teacher observation and dialogue remain essential for interpreting these signals. Artificial intelligence can make teaching more responsive, but professional judgement determines when adaptation supports independence and when it risks producing dependence.

Adaptive support is credible only when it helps students progress toward common academic standards without creating dependency on automated guidance.

Responsiveness becomes more powerful when adaptive support is incorporated into the architecture of a course rather than offered as an optional technological add-on. Educators can design learning sequences in which students first attempt a task independently, then obtain structured AI assistance, compare their revised reasoning with disciplinary criteria, and finally explain what changed in their understanding. This preserves a visible learning process while allowing personalised support. Chiu (2024) argues that higher education should develop new literacies and pedagogies around generative artificial intelligence, which supports the view that adaptation must be accompanied by explicit learning about the technology itself. Student differences also make equity central. Advanced systems may be available through paid subscriptions, while language proficiency and prior digital experience can influence the quality of interaction. Institutional provision should therefore avoid creating a situation in which adaptation benefits already advantaged students most. Research on digital participation in university contexts shows that technology interacts with broader patterns of access and behaviour rather than operating independently of them (Yusof et al., 2025). A credible adaptive model combines access, pedagogical sequencing, transparent expectations, and teacher oversight. Its objective is not to personalise every element of learning, but to provide timely support that helps more students reach demanding academic outcomes through progressively greater independence. Responsiveness should ultimately strengthen learner independence by making support timely, transparent, and progressively less necessary as competence develops.

2.3 Assessment Redesign Protecting Authentic Academic Learning Processes

Assessment requires fundamental reconsideration because generative artificial intelligence can produce essays, summaries, code, calculations, presentations, and other artefacts that once served as indirect evidence of student capability. When the final product can be heavily shaped by an external system, educators need stronger evidence of how students reasoned, selected information, verified claims, and made decisions. Xia et al. (2024) conclude that generative artificial intelligence is transforming assessment in higher education and emphasise self-regulated learning, responsible learning, and integrity. Bower et al. (2024) likewise report educator support for substantial changes in assessment. The strongest response is not to abandon take-home work but to diversify evidence. Oral explanation, staged submissions, annotated drafts, reflective commentaries, supervised problem solving, process logs, and authentic projects can reveal dimensions of learning that are difficult to outsource invisibly. Assessment tasks can also incorporate artificial intelligence explicitly by requiring students to critique a generated response, justify revisions, or compare AI-supported and independent solutions. These approaches shift emphasis from possession of a polished artefact toward demonstrated judgement. The educator's role becomes more interpretive because assessment design must identify which intellectual processes matter most within a discipline. Artificial intelligence therefore exposes weaknesses that were already present in product-dominated assessment and creates an opportunity to make assessment more closely aligned with genuine competence. Assessment redesign is successful when the evidence collected still allows educators to make defensible judgements about what students genuinely know and can do.

Authenticity does not require every task to be completed without artificial intelligence. In many professions, graduates will work with automated systems, making responsible AI use part of real-

world capability. The assessment challenge is to distinguish legitimate tool use from substitution of the learner's own judgement. Bhullar et al. (2024) show that academic integrity has become a central concern in the higher education literature on ChatGPT, but integrity is difficult to protect when rules are vague or inconsistent across modules. Students need explicit statements about permitted assistance, disclosure, verification, attribution, and the parts of a task that must demonstrate independent competence. Educators also need assessment designs that make undisclosed substitution less rewarding. For example, a written report can be paired with an oral defence; a coding task can include live modification; a project can require process evidence; or a reflective commentary can connect decisions to course concepts. Kamarudin et al. (2025) demonstrate the value of hands-on, action-oriented learning in university contexts, reinforcing the broader importance of observable student participation. Assessment becomes more credible when it captures performance over time and across modes. The objective is not surveillance. It is to produce trustworthy evidence that a student can think, explain, evaluate, create, and take responsibility for academic decisions in an environment where artificial intelligence is readily available. Authenticity therefore depends on visible reasoning, accountable tool use, and assessment choices that preserve meaningful evidence of student capability.

2.4 Educator Capability Strengthening Responsible Artificial Intelligence Integration

Educator capability is a prerequisite for responsible artificial intelligence integration because teachers cannot guide students through practices, they do not understand themselves. Capability extends beyond basic tool operation. It includes knowledge of model limitations, prompt design, verification, bias, privacy, assessment implications, disciplinary appropriateness, and the ability to judge whether an AI-supported activity improves learning. Ren and Wu (2025) identify teaching competencies as central to AI integration in higher education, while Ellis et al. (2025) show that educators experience generative artificial intelligence in markedly different ways. Such variation is predictable because disciplines differ in epistemology, assessment conventions, technical practices, and tolerance for automation. A lecturer in law may be especially concerned with authority and citation; a computing lecturer may focus on code explanation and debugging; a design educator may explore ideation while protecting authorship and originality. Professional development should therefore avoid generic demonstrations that treat all teaching contexts as equivalent. Educators need opportunities to test tools against real course tasks, examine failure cases, compare disciplinary practices, and redesign activities with colleagues. Research on technology adoption emphasises that organisational value depends on capability development rather than acquisition alone (Yusof, 2025a). Higher education should apply the same principle by treating AI competence as an evolving professional capability embedded within academic practice. Educator capability should be visible in the quality of pedagogical decisions, not in the frequency with which artificial intelligence is used.

Capability also includes the confidence to reject artificial intelligence when it is pedagogically inappropriate. Technology adoption can create subtle pressure to use new systems because they are visible, fashionable, or associated with innovation. Professional judgement requires the opposite discipline: educators should be able to explain why a conventional seminar, laboratory activity, supervised writing task, field exercise, or direct human feedback process is superior for a particular outcome. Bayaga (2025) connects emerging technologies with pedagogical innovation, but innovation should be evaluated through educational contribution rather than novelty. Continuous experimentation is useful when it is accompanied by evidence, reflection, and peer dialogue.

Universities can support this by creating communities of practice, disciplinary showcases, mentoring arrangements, shared repositories of tested activities, and workload recognition for redesign. Human-centred work research also reminds institutions that capability development depends on the conditions under which professionals are expected to perform (Abd Wahab & Yusof, 2020). If educators are given ambitious AI expectations without time, support, or reliable infrastructure, adoption may become superficial. Sustainable capability develops when teachers can experiment safely, discuss uncertainty openly, and refine practice over repeated cycles. The objective is not universal enthusiasm for artificial intelligence, but informed professional discretion grounded in pedagogy, ethics, disciplinary standards, and evidence of learning. Such discretion enables educators to adopt, adapt, question, or reject AI-supported practices according to their educational value while preserving professional accountability for the quality of teaching.

2.5 Human Judgement Preserving Educational Purpose Automation Accountability

Human judgement remains the decisive safeguard in artificial intelligence-supported teaching because educational decisions involve values and contextual interpretation that cannot be reduced to generated output. Educators decide what knowledge is important, how much challenge is appropriate, whether feedback is fair, when a student needs encouragement, and how disciplinary standards should be applied in ambiguous cases. Artificial intelligence can assist with options and information, but responsibility for those decisions remains human. Kasneci et al. (2023) highlight reliability and ethical concerns associated with large language models, while Tlili et al. (2023) show that educational use requires careful attention to both opportunity and risk. The distinction is especially important when generated material appears authoritative. Fluency can create an illusion of certainty, encouraging educators or students to accept claims before checking evidence. Professional judgement introduces epistemic restraint by asking whether a response is accurate, relevant, sufficiently nuanced, and appropriate for the learner. It also protects students from inappropriate automation of sensitive interactions involving wellbeing, disability, conflict, or high-stakes academic decisions. Ethical leadership research emphasises that technological systems should operate within clear professional values and accountability (Yusof & Abd Wahab, 2020). In higher education, artificial intelligence should therefore remain subordinate to educational purpose and human responsibility, even when its technical performance appears impressive. Human judgement remains indispensable wherever academic decisions require interpretation, fairness, contextual sensitivity, or responsibility for their educational consequences.

Preserving human judgement does not mean maintaining traditional practices unchanged. Artificial intelligence can remove routine burdens and create more space for activities that benefit from direct educator attention, such as discussion, mentoring, complex feedback, and interpretation of student reasoning. The challenge is to decide what should be automated and what should remain deliberately human. A useful criterion is educational consequence. Low-risk administrative drafting may be suitable for automation after review, whereas feedback affecting progression, grading, or student identity requires stronger human oversight. Chiu (2024) argues that future higher education must develop AI literacy and new pedagogical approaches, which implies that judgement itself should become an explicit learning outcome. Students need practice evaluating generated claims, recognising uncertainty, and deciding when human expertise is indispensable. Yusof and Razali (2020) show the importance of managerial judgement under organisational uncertainty, a principle that resonates with academic decision making under rapidly changing technological conditions.

Human judgement becomes more valuable, not less, as AI capability increases because educators must interpret a wider range of machine-produced possibilities. The mature model of AI-supported teaching is therefore neither teacher replacement nor simple tool adoption. It is a professional arrangement in which computational assistance expands options while educators remain accountable for academic standards, learner development, fairness, and the meaning of educational decisions. The mature use of artificial intelligence therefore strengthens professional judgement instead of creating conditions in which judgement is quietly outsourced.

3.0 PRESSURES DISRUPTING RESPONSIBLE AI ENABLED TEACHING TRANSFORMATION

The disruptive potential of artificial intelligence becomes visible when its use is detached from learning purposes, epistemic standards, fair access, and clear institutional expectations. Pedagogical misalignment can turn innovation into activity without educational value; unreliable outputs can contaminate learning with confident error; integrity problems can weaken conventional evidence of authorship; unequal capability can create inconsistent learning opportunities; and uncertain governance can leave educators unsure about legitimate practice. These problems are connected by a common weakness: technology moves quickly while pedagogical routines and institutional systems adapt more slowly. Bhullar et al. (2024) and Xia et al. (2024) show that integrity, assessment, and policy concerns are already central in higher education. Ren and Wu (2025) add that educator competencies strongly influence the quality of integration. The challenge is therefore not simply controlling artificial intelligence. Universities must protect the conditions that make academic learning credible, including transparent expectations, verifiable knowledge, meaningful student contribution, equitable support, and professional discretion.

3.1 Pedagogical Misalignment Weakening Meaningful Artificial Intelligence Adoption

Pedagogical misalignment occurs when artificial intelligence is introduced because it can be used, rather than because a particular learning problem justifies its use. Tool-first adoption often produces activities that are technologically visible but educationally thin. Students may spend time prompting a system, generating text, or experimenting with features without developing the disciplinary reasoning intended by the course. Qian (2025) shows that pedagogical applications of generative artificial intelligence are diverse, but diversity should not be mistaken for effectiveness. Every use requires a clear account of what students should understand, what intellectual work they should perform, and how AI participation changes that work. Misalignment is especially likely when institutions encourage rapid innovation without giving educators time to redesign curricula. The result can be superficial substitution, such as replacing a conventional worksheet with an AI-generated worksheet while leaving the underlying pedagogy unchanged. A stronger approach begins with the learning outcome and works backward. Educators should identify the difficulty students need to confront, the evidence that will demonstrate learning, and the point at which artificial intelligence can provide support without removing essential reasoning. Digital transformation research shows that technology adoption is most valuable when aligned with organisational purpose and capability (Yusof, 2025a). The same discipline is necessary in higher education, where pedagogical purpose must remain the criterion for adoption. Pedagogical alignment gives artificial intelligence a clear educational purpose and prevents technological activity from becoming mistaken for meaningful innovation.

Misalignment also appears when different parts of a course communicate contradictory expectations. A lecturer may encourage AI-assisted brainstorming in class while an assessment brief prohibits all use, or students may receive automated feedback even though they are discouraged from using similar tools themselves. Such contradictions make it difficult to understand the educational rationale behind institutional rules. Bower et al. (2024) demonstrate that teachers expect generative artificial intelligence to change both teaching and assessment, which means that these practices must be redesigned coherently rather than separately. Curriculum, assessment, feedback, and academic integrity policy should communicate a consistent philosophy of student responsibility. Students need to know which tasks are designed to develop independent capability, which permit AI support, and why those distinctions exist. Pedagogical coherence also requires attention to sequencing. Beginners may need more protected opportunities for unaided practice before using generative systems, whereas advanced students can be expected to evaluate and integrate AI outputs critically. Institutional learning research suggests that innovation becomes stronger when organisations revise routines in response to evidence rather than simply adding new procedures (Yusof, 2007). Universities should therefore evaluate AI-supported teaching by examining the quality of student reasoning and learning outcomes, not the amount of technological activity. Alignment gives innovation educational direction and prevents artificial intelligence from becoming an end in itself. Coherent curriculum design is therefore essential if students are to understand why AI is permitted, restricted, or required within different learning tasks.

3.2 Unreliable Outputs Compromising Academic Knowledge Verification Practices

Unreliable output is an educational problem because generative systems can present inaccurate information in fluent and persuasive language. Students who lack sufficient disciplinary knowledge may be unable to distinguish a plausible explanation from a correct one, making the technology potentially more misleading at the very stage when learners are most dependent on guidance. Kasneci et al. (2023) identify hallucination and reliability as important limitations of large language models, while Almasri (2024) notes that effective educational use requires careful consideration of accuracy and pedagogical context. The risk is not confined to factual error. Generated responses may oversimplify contested knowledge, omit minority perspectives, fabricate citations, or present one interpretation as settled when a field is genuinely uncertain. Educators must therefore treat AI output as provisional material requiring verification rather than as an authoritative source. This principle should be taught explicitly. Students can learn to trace claims to original sources, compare outputs with scholarly literature, test calculations, and explain why a response is or is not trustworthy. Verification becomes part of disciplinary literacy because standards of evidence differ across fields. A reliable teaching environment does not ask students merely to use artificial intelligence carefully. It provides concrete routines for checking claims and makes responsibility for verification visible in learning activities and assessment. Reliable teaching requires generated claims to remain open to challenge until they are supported by appropriate disciplinary evidence.

The epistemic challenge becomes more serious when artificial intelligence is integrated into routine teaching workflows. If educators use generated explanations, quiz items, feedback comments, or references without systematic checking, errors can be reproduced at scale and acquire institutional legitimacy. Qian (2025) shows how broadly generative tools can enter pedagogical practice, which increases the importance of quality assurance at the point of use. Verification should therefore be designed as a professional routine rather than left to individual caution. Educators can compare

generated material with authoritative scholarship, use multiple sources, inspect original references, and subject unfamiliar claims to disciplinary review. Students should encounter the same expectations in their academic work. This creates a culture in which confidence is not confused with evidence. Research on technological learning highlights the importance of building capability through repeated interaction and evaluation rather than passive adoption (Yusof, Razak, & Fauzi, 2025). That principle is directly relevant to AI-supported knowledge work. Institutions should also avoid policies that imply approved tools are inherently accurate; procurement and security review do not guarantee epistemic reliability. The educational objective is to cultivate verification as a normal part of academic reasoning. When students and educators learn to interrogate generated output, artificial intelligence can stimulate inquiry without weakening the standards by which knowledge claims are judged. Epistemic vigilance becomes a core academic capability when students and educators routinely distinguish fluent presentation from trustworthy knowledge.

3.3 Academic Integrity Pressures Destabilising Conventional Assessment Practices

Academic integrity is destabilised when conventional assessment assumes that the submitted product directly reflects the student's own intellectual process. Generative artificial intelligence weakens that assumption because polished text, code, images, and solutions can be produced with minimal visible evidence of authorship. Bhullar et al. (2024) identify plagiarism and integrity as prominent concerns in higher education, while Xia et al. (2024) show that assessment reform is increasingly connected with responsible learning and self-regulation. The problem should not be reduced to misconduct detection. Universities need to clarify what counts as legitimate assistance within different tasks and disciplines. Some activities may permit AI for language refinement, brainstorming, or coding support; others may require unaided performance because the capability itself is being assessed. Integrity becomes more defensible when these distinctions are explicit before students begin the task. Disclosure practices can also help by requiring students to explain where AI was used, what outputs were accepted or rejected, and how claims were verified. Such transparency changes the emphasis from hidden tool use toward accountable decision making. The deeper objective is to preserve meaningful evidence of learning, not to create a technology-free environment. Assessment should reveal what the student understands and can justify even when artificial intelligence participates in parts of the workflow. Academic integrity is better protected by credible evidence of learning than by assumptions that technological use can always be detected after submission.

Integrity policy loses credibility when it relies on inconsistent rules, unverifiable detection, or assumptions that all AI use has the same academic meaning. Students may encounter different expectations across courses, while educators themselves may be uncertain about permissible practice. Bower et al. (2024) show that generative artificial intelligence is already prompting educators to reconsider assessment design rather than simply strengthen policing. Authenticity can be improved through staged tasks, oral explanation, reflective commentary, process evidence, supervised performance, and assignments linked to local or personal contexts. These approaches reduce the value of submitting generic generated work because students must demonstrate ownership of reasoning. Kamarudin et al. (2025) provide evidence from university learning that active, hands-on participation can strengthen engagement and capability, supporting assessment designs that observe students doing rather than merely submitting. Integrity also requires fairness. Students should not be penalised for using tools that educators have not clearly addressed, and policies should recognise accessibility uses where appropriate. A credible academic integrity framework combines

explicit expectations, task redesign, student education, proportionate accountability, and opportunities for students to demonstrate how their work was produced. Artificial intelligence can then be treated as part of a wider academic conversation about authorship, evidence, responsibility, and professional ethics rather than reduced to a narrow problem of technological cheating. Clear expectations established before assessment begins strengthen fairness while rewarding students who can explain, verify, and defend the intellectual decisions represented in their work.

3.4 Capability Inequality Producing Uneven Teaching Transformation Outcomes

Capability inequality can produce uneven teaching transformation even when institutions provide access to the same artificial intelligence platform. Educators differ in confidence, disciplinary experience, technical fluency, workload, and opportunities for professional learning. Ren and Wu (2025) show that AI integration depends on a combination of teaching competencies and the ability to manage new challenges. These differences matter because artificial intelligence is not self-explanatory. An experienced user may recognise hallucinations, design effective prompts, and integrate outputs into coherent pedagogy, while another may use the same system mainly for superficial content generation. Disciplinary context further complicates the picture. Fields with established computational practices may adapt quickly, whereas disciplines centred on interpretive judgement, studio work, laboratory activity, or professional accreditation may face different questions. Institutions should therefore avoid using adoption rates as a proxy for educational progress. Capability needs to be evaluated through the quality of teaching decisions and the educator's ability to explain why AI is or is not appropriate for a particular task. Research on digital transformation demonstrates that organisational outcomes depend on human and managerial capability as much as on technology itself (Yusof, 2026). Higher education needs differentiated support that recognises disciplinary variation while establishing common standards for verification, ethics, and student responsibility. Capability inequality should therefore be treated as an educational quality problem rather than a simple difference in individual enthusiasm for technology.

Student inequality is equally important because the benefits of AI-supported learning are shaped by access, language, prior knowledge, digital confidence, disability, and the quality of guidance available. Paid tools may offer stronger features than free versions, potentially creating hidden advantages in courses where AI use is expected. Students with stronger disciplinary knowledge can also evaluate generated responses more effectively, while beginners may be more vulnerable to confident errors. Chiu (2024) emphasises AI literacy as an important future capability, suggesting that universities cannot assume students acquire responsible competence simply through exposure. Equity therefore requires structured learning opportunities in which all students practise verification, prompting, disclosure, and critical evaluation. Research on digital mobility among university students indicates that technology use is embedded within broader behavioural and educational contexts (Yusof et al., 2025). The same applies to generative artificial intelligence. Access without guidance can reproduce rather than reduce disadvantage. Universities should provide baseline access where AI is integral to coursework, offer alternatives where students cannot or do not wish to use particular systems, and ensure that assessment does not reward subscription level. Capability equality is not achieved by distributing accounts. It requires pedagogical support, transparent expectations, accessible infrastructure, and sufficient opportunity for students to develop informed judgement across different levels of prior experience. Equitable transformation requires comparable opportunities to develop judgement, not merely equal access to the same digital platform.

3.5 Governance Uncertainty Constraining Responsible Pedagogical Innovation Practices

Governance uncertainty constrains responsible innovation because educators and students cannot make confident decisions when institutional expectations are unclear, contradictory, or excessively broad. Policies that simply prohibit or permit artificial intelligence fail to address the diversity of academic tasks. A tool may be appropriate for brainstorming in one context, unacceptable during a competency test, and mandatory in another task designed to assess professional AI use. Chiu (2024) argues that higher education must reconsider policy alongside pedagogy, assessment, and future competencies. Effective governance should therefore define durable principles rather than attempt to anticipate every tool or scenario. Core principles can address transparency, privacy, academic responsibility, verification, human oversight, accessibility, and protection of sensitive information. These principles require disciplinary interpretation because acceptable assistance depends on what a course is intended to assess. Governance also needs procedural clarity. Educators should know who can approve new uses, how concerns are escalated, and how expectations are revised as systems change. Corporate governance research emphasises that accountability and transparency support sustainable organisational development (Yusof, Abdul Razak, Misnan, & Abdul Malik, 2026). Comparable principles are relevant to universities because transparent responsibilities create a stable basis for experimentation without freezing pedagogy into inflexible rules. Credible governance therefore combines common institutional standards with sufficient academic discretion to accommodate disciplinary differences, changing technologies, and legitimate variation in educational purpose.

Overly rigid governance can be as damaging as ambiguity. Artificial intelligence develops too quickly for static lists of approved or banned practices to remain useful, and detailed rules can discourage legitimate pedagogical experimentation. A stronger model combines institutional boundaries with professional discretion. Educators can be given common requirements for privacy, disclosure, assessment integrity, and verification while retaining authority to decide how those requirements are implemented within disciplinary contexts. Ellis et al. (2025) show that teachers experience generative artificial intelligence differently, reinforcing the need for governance that accommodates variation rather than enforcing superficial uniformity. Ethical leadership is also central because institutions must model the transparency they expect from students. If universities deploy automated systems in teaching, advising, or assessment, they should explain their purpose and limitations. Yusof and Abd Wahab (2020) emphasise professional integrity as a foundation of credible management, a principle directly relevant to AI governance. Policy should be reviewed through evidence from actual teaching practice, student feedback, incidents, and disciplinary developments. This creates adaptive governance rather than compliance alone. The objective is to enable innovation within trustworthy boundaries, giving educators enough freedom to redesign teaching while protecting academic standards, student rights, and institutional accountability. Adaptive policy is therefore more sustainable than static rules because technological capability, teaching practice, and academic risk continue to evolve together. Policy clarity is strongest when institutional principles can be translated into consistent decisions without suppressing legitimate disciplinary variation.

4.0 MECHANISMS TRANSFORMING AI CAPABILITY EDUCATIONAL VALUE CREATION

Educational value emerges when artificial intelligence is mediated by capabilities that connect technological possibility with disciplined teaching practice. Teacher agency determines why a tool is used and what learning purpose it should serve. Verification capability protects academic knowledge from plausible error. Authentic assessment makes student reasoning, decision making, and disciplinary judgement visible despite easy access to generated content. Professional learning enables educators to develop these practices through experimentation, reflection, and peer exchange. Institutional coordination aligns policy, infrastructure, workload, and academic standards so that individual educators are not left to manage complex risks alone. Ellis et al. (2025) show that teacher experiences with generative artificial intelligence vary substantially, while Ren and Wu (2025) identify competencies that condition successful integration. These findings reinforce a broader principle found in digital capability research: technology produces sustainable value when human capability and organisational arrangements evolve with it (Yusof, 2025a). The crucial transformation therefore occurs in professional and institutional practice, not simply in the acquisition of new systems.

4.1 Teacher Agency Transforming Artificial Intelligence Pedagogical Practice

Teacher agency explains why identical artificial intelligence systems can produce very different educational outcomes. Educators decide whether a generated response becomes a model answer, a flawed text for critique, a source of alternative examples, or material that should not be used at all. Agency therefore operates through purposeful selection, interpretation, adaptation, and refusal. Bower et al. (2024) show that educators hold varied views about how teaching should change in response to generative artificial intelligence, while Ellis et al. (2025) identify qualitatively different experiences of teaching with these systems. Such variation is not a weakness to be eliminated; it reflects the professional judgement required by different disciplines and learner groups. Agency becomes productive when educators can explain the pedagogical reason for AI use, anticipate its effects on student effort, and revise practice when evidence suggests that learning is being weakened. Institutions should avoid converting AI integration into a checklist that rewards visible use regardless of educational value. Teacher agency is also necessary for protecting boundaries. Educators may decide that some tasks require direct human dialogue, independent writing, laboratory performance, or supervised problem solving. The ability to make those distinctions preserves academic purpose. Artificial intelligence transforms teaching most effectively when it expands professional options while leaving educators accountable for the educational consequences of those choices. Teacher agency gives artificial intelligence pedagogical direction by linking every technological choice to explicit educational purposes and professional accountability.

Agency also shapes how students learn to exercise responsibility around artificial intelligence. Educators model epistemic behaviour when they show how generated material is questioned, verified, revised, or rejected. This modelling is particularly important because students may otherwise interpret technological confidence as evidence of correctness. Qian (2025) documents broad pedagogical applications of generative AI, but meaningful use requires teachers to frame those applications within disciplinary standards. A lecturer can make reasoning visible by comparing an AI-generated answer with an expert explanation, tracing unsupported claims, or discussing why a prompt produced an incomplete response. These practices turn teacher agency into a form of

intellectual apprenticeship. Research on organisational learning suggests that capability develops when people can experiment, reflect, exchange knowledge, and revise routines (Yusof, 2007). The same process should characterise academic adoption of artificial intelligence. Educators need space to test practices, share failures, and learn from disciplinary peers. Agency is weakened when policy is so restrictive that experimentation becomes risky, but it is also weakened when institutions provide no guidance and leave individuals to carry all responsibility. A balanced environment combines professional discretion with shared standards. This allows teachers to innovate while preserving academic integrity, student welfare, and the credibility of learning outcomes. Agency remains strongest when educators can experiment, refuse unsuitable uses, and revise practice according to evidence from actual student learning.

4.2 Verification Capability Sustaining Trustworthy AI Supported Teaching

Verification capability converts artificial intelligence from a source of plausible text into a usable academic resource. The capability involves checking factual claims, tracing references, comparing outputs with authoritative sources, testing calculations, identifying missing perspectives, and recognising when uncertainty should remain unresolved. Kasneci et al. (2023) emphasise that large language models can generate convincing but unreliable information, while Almasri (2024) shows that educational benefits depend on careful implementation. Verification is therefore not a technical afterthought. It is part of the intellectual work required to use generative systems responsibly. Educators should model different verification strategies according to discipline. A historian may examine provenance and primary evidence; a scientist may check mechanisms and empirical support; a lawyer may verify jurisdiction and precedent; a programmer may test code against specifications. These practices help students understand that AI output has no special exemption from normal standards of evidence. Verification also changes feedback. Instead of correcting every generated error for students, educators can require them to explain how they tested a claim and why a source should be trusted. This shifts responsibility back toward the learner. The most valuable AI-supported teaching therefore treats verification as a transferable academic capability that strengthens critical thinking, information literacy, and professional judgement. Verification capability protects academic trust by ensuring that generated information remains subordinate to evidence rather than fluency or computational authority.

Institutionalising verification requires more than advising students to double-check answers. Universities can embed explicit verification criteria within rubrics, assessment briefs, academic literacy programmes, library support, and professional development. Qian (2025) shows that generative artificial intelligence is becoming part of multiple pedagogical activities, which means verification needs to travel across the curriculum rather than remain confined to specialist courses. Students should encounter progressively demanding expectations: beginners may compare outputs with provided readings, intermediate learners may locate independent evidence, and advanced students may evaluate conflicting sources or methodological claims. Educators also need support because generated references and technical claims can be difficult to inspect quickly. Shared resources, librarian collaboration, discipline-based examples, and peer review of AI-supported materials can reduce this burden. Yusof, Abdul Razak, Jamaludin, et al. (2025) highlight system maintenance and security challenges in smart technology adoption, illustrating a broader principle that technological systems require continuing oversight rather than one-time acceptance. In higher education, epistemic oversight is equally necessary because fluent output can conceal factual

weakness or unsupported reasoning. Verification routines should become normal academic practice whenever AI participates in knowledge production. This protects students from error while reinforcing a fundamental scholarly principle: credible knowledge depends on evidence, traceability, critical evaluation, and accountable judgement rather than confidence of presentation. Embedded verification can consequently make artificial intelligence a stimulus for stronger scholarly judgement instead of a reason for weaker source discipline.

4.3 Authentic Assessment Reinforcing Student Ownership Learning Integrity

Authentic assessment protects student ownership of learning by requiring performance that reflects situated judgement, explanation, application, or creation rather than reproduction of generic content. Generative artificial intelligence makes this principle increasingly important because conventional essays and unsupervised written tasks can be produced with substantial machine assistance. Xia et al. (2024) show that assessment reform is one of the clearest areas of transformation in higher education. Authenticity can be strengthened by linking tasks to real problems, local data, personal decisions, disciplinary artefacts, live interaction, or iterative project work. Students can be required to defend choices, explain alternatives, respond to follow-up questions, or demonstrate how feedback changed their work. These features make learning visible across time rather than at a single submission point. Artificial intelligence can still be incorporated where it reflects professional practice, but the student must remain responsible for evaluating and transforming the output. For example, a business student might compare AI-generated strategic options and justify one using evidence; an engineering student might test a generated design against constraints; a language student might analyse machine translation errors. Authentic assessment therefore does not exclude artificial intelligence. It changes the evidential burden so that competence is demonstrated through accountable performance rather than the appearance of a polished final product. Authentic assessment preserves student ownership by requiring forms of performance that cannot be reduced to the possession of a polished generated artefact.

Student ownership is reinforced when assessment requires reflection on the use of artificial intelligence itself. A process commentary can ask students what prompts they used, what outputs they rejected, how they verified information, and which decisions remained independently theirs. Such requirements encourage metacognition because learners must reconstruct the reasoning behind their work. Bower et al. (2024) report educator support for changing assessment in response to increasingly powerful generative AI, while Kamarudin et al. (2025) demonstrate the educational value of active, hands-on learning. These ideas converge around the importance of observable participation. Universities should therefore design assessment ecosystems rather than rely on a single high-stakes product. Portfolios, oral defences, workshops, peer critique, supervised components, and iterative submissions can collectively provide stronger evidence of learning. The approach also reduces dependence on unreliable AI-detection tools because judgement is based on richer evidence. Authenticity should remain proportionate; not every task needs elaborate redesign. The priority is to identify where generated content can most easily obscure the capability being assessed and strengthen evidence at those points. When students know that they must explain and defend their work, artificial intelligence is more likely to support learning than substitute for it. Multiple forms of evidence consequently strengthen confidence that grades represent demonstrated capability, intellectual judgement, and meaningful learning rather than undisclosed technological substitution.

4.4 Professional Learning Transforming Technology Access Educator Capability

Professional learning determines whether technology access develops into educational capability. Short demonstrations can familiarise educators with features, but they rarely address the deeper questions of pedagogy, assessment, verification, privacy, and disciplinary appropriateness. Ren and Wu (2025) show that teaching competencies are central to AI integration, while Ellis et al. (2025) reveal considerable variation in teacher experience. Professional development should therefore be iterative and practice-based. Educators need opportunities to redesign a real activity, test it with students, examine outcomes, and discuss what worked with colleagues. Discipline-based communities are especially valuable because they allow staff to explore shared epistemic and assessment concerns. Cross-disciplinary exchange also matters, particularly for issues such as disclosure, bias, privacy, and student equity. Human-centred work research indicates that professional performance depends on supportive work design rather than expectations alone (Abd Wahab & Yusof, 2020). Universities should recognise this by providing time, technical assistance, accessible guidance, and workload consideration for substantial curriculum redesign. Professional learning becomes sustainable when educators can move from curiosity to informed experimentation and then to evidence-based refinement. The objective is not to produce identical practice across the institution, but to ensure that every educator has the capability to make responsible decisions about artificial intelligence within their own teaching context. Professional learning becomes transformative when educators repeatedly test practice, examine consequences, and refine decisions within supportive academic communities.

Professional learning should also include failure. Artificial intelligence often produces impressive first demonstrations, which can create overconfidence before educators encounter hallucination, bias, privacy limitations, or unanticipated student behaviour. Structured exploration of failure cases helps staff develop realistic expectations and more robust judgement. Almasri (2024) and Kasneci et al. (2023) both highlight limitations that need to accompany discussion of educational opportunity. Educators can benefit from workshops in which they deliberately test systems with ambiguous prompts, contested topics, incorrect assumptions, or discipline-specific tasks. They can then compare outputs and develop strategies for verification and redesign. Organisational learning research similarly emphasises experimentation, knowledge sharing, and revision as foundations of innovation (Yusof, 2007). Professional learning should therefore continue after initial implementation. Communities of practice can collect examples, monitor changing tools, and update guidance as new capabilities emerge. Mentoring can support less confident staff without framing them as resistant. Recognition systems should also value thoughtful non-use where an educator can justify why artificial intelligence would weaken a particular learning outcome. Mature capability includes knowing when not to automate. Universities that cultivate this reflective professional culture are more likely to achieve durable transformation than institutions that equate innovation with the number of AI tools adopted. Sustainable capability depends on continuous professional dialogue because the educational implications of artificial intelligence will not remain technically or pedagogically stable.

4.5 Institutional Coordination Balancing Innovation Accountability Educational Trust

Institutional coordination is necessary because artificial intelligence affects multiple parts of higher education simultaneously. Teaching policy, assessment regulation, academic integrity, information security, procurement, accessibility, staff development, student support, and quality assurance can

no longer operate independently when the same systems touch all of them. Fragmented governance creates contradictory expectations and transfers the burden of interpretation to individual educators. Chiu (2024) emphasises that generative artificial intelligence requires higher education to rethink policy alongside learning outcomes and pedagogy. Coordination should therefore connect central principles with disciplinary implementation. A university may establish common expectations for privacy, transparency, verification, and human responsibility while allowing faculties to specify appropriate uses within their fields. This arrangement protects consistency without forcing identical pedagogy. Governance research highlights the role of transparency and accountability in sustainable organisational development (Yusof, Abdul Razak, Misnan, & Abdul Malik, 2026). Those principles are relevant to universities because students should understand how expectations relate across modules and staff should know where authoritative guidance can be obtained. Coordination is not simply administrative efficiency. It creates institutional trust by aligning policy, technological infrastructure, assessment expectations, professional support, and classroom practice around coherent educational principles. Such alignment reduces contradictory messages, clarifies responsibility, and gives educators a more dependable environment in which responsible pedagogical innovation can develop.

Coordination also requires mechanisms for institutional learning because artificial intelligence will continue to change after policies are written. Universities should collect evidence from pilots, assessment reviews, student feedback, academic integrity cases, accessibility concerns, and educator experience. This information can support periodic revision rather than reactive rule making. Ellis et al. (2025) show that educator experiences are diverse, so governance should learn from differences instead of assuming one model fits every context. Leadership capability matters because decisions involve competing priorities such as innovation, risk, workload, cost, and academic standards. Yusof (2026) argues that digital leadership contributes to organisational performance when technology and leadership capabilities are integrated. In higher education, leaders need enough technological understanding to ask informed questions while respecting academic expertise. Coordination should also include libraries, learning designers, IT specialists, student services, and educators because responsible use crosses professional boundaries. The goal is a coherent institutional environment in which innovation can occur without uncertainty about basic responsibilities. When policies, support systems, assessment expectations, and professional development reinforce one another, educators can focus on teaching quality rather than repeatedly resolving institutional ambiguity at the classroom level. Coherence reduces uncertainty for educators while allowing disciplinary differences to shape the practical expression of shared institutional standards. Coordinated implementation is strongest when academic, technical, and governance functions share evidence and respond to emerging problems collectively.

5.0 STRATEGIC PATHWAYS STRENGTHENING RESPONSIBLE AI TEACHING CAPABILITY

Sustainable artificial intelligence integration requires universities to embed pedagogical purpose, verification, authentic assessment, educator development, and accountable governance within normal academic practice. One-off workshops or isolated experiments are unlikely to produce durable improvement because generative systems affect curriculum design, feedback, assessment, academic integrity, and professional roles simultaneously. Bower et al. (2024) indicate that educators expect substantial changes in teaching and assessment, while Ren and Wu (2025) emphasise the

competencies required for responsible integration. Practical progress depends on institutional routines that make those competencies usable: curriculum teams need clear learning outcomes, educators need access to professional learning, students need transparent expectations, and assessment needs evidence that remains meaningful when AI assistance is available. Governance must also be adaptive because the capabilities of systems will continue to change. Digital transformation research highlights the importance of combining technological adoption with organisational learning and leadership capability (Yusof, 2026). Higher education needs the same capacity to learn from implementation, revise weak practices, and preserve academic standards while innovation continues.

5.1 Purposeful Curriculum Integration Embedding Artificial Intelligence Pedagogy

Purposeful curriculum integration begins by identifying where artificial intelligence contributes to the capabilities graduates genuinely need. It should not be inserted into every module simply because it is widely available. Curriculum teams need to decide which learning outcomes require independent mastery, which involve responsible AI collaboration, and which demand critical understanding of how automated systems shape professional practice. Chiu (2024) argues that future higher education should incorporate AI literacy and new learning outcomes, while Qian (2025) shows that pedagogical applications already extend across diverse learning activities. Integration can therefore occur at several levels. Students may learn about AI limitations, use AI as a tool within disciplinary work, critique AI-generated outputs, or design solutions that combine human and computational judgement. Sequencing is important. Foundational courses may emphasise independent knowledge and verification before students engage in more complex AI-supported tasks. Advanced courses can require students to justify tool selection and evaluate ethical consequences. Curriculum integration should also connect with assessment so that expected forms of AI use are visible in the evidence students must produce. This avoids the contradiction of teaching AI-supported professional practice while assessing as though the technology does not exist. Purposeful integration gives artificial intelligence a clear educational role and protects the curriculum from technology-driven drift. Curriculum integration should therefore produce graduates who can use artificial intelligence critically without losing the independent capabilities their disciplines still require.

Disciplinary ownership is essential because artificial intelligence has different implications across fields. The standards for evidence, originality, professional risk, and acceptable automation differ between medicine, engineering, law, business, design, humanities, and education. A common institutional AI literacy framework can establish shared principles, but curriculum teams should translate those principles into authentic disciplinary practice. Ren and Wu (2025) show that educator competencies influence integration, reinforcing the need for staff involvement in curriculum decisions. Students should encounter examples that reflect the actual knowledge problems of their field rather than generic prompting exercises. They might evaluate fabricated citations, compare competing interpretations, identify bias in a recommendation, verify quantitative outputs, or explain why a generated solution violates professional standards. Technology adoption research indicates that value emerges when digital capability is aligned with the specific requirements of organisational activity (Yusof, 2025a). Curriculum design requires the same fit. Integration should also be reviewed regularly because professional uses of artificial intelligence will evolve. Advisory input from employers, professional bodies, alumni, and students can help identify emerging expectations, but academic judgement should determine how those expectations become learning outcomes. The

result should be graduates who can work with artificial intelligence without becoming dependent on it and who understand when disciplinary responsibility requires them to question, override, or reject automated output. Disciplinary ownership keeps AI literacy connected to authentic knowledge problems rather than reducing curriculum reform to generic technology training.

5.2 Evidence Verification Routines Strengthening Academic Knowledge Reliability

Evidence verification should be embedded as a routine academic expectation whenever artificial intelligence participates in knowledge production. Students need a repeatable process that moves from generated claim to source checking, comparison, evaluation, and documented judgement. Kasneci et al. (2023) show why this is necessary by highlighting the reliability limitations of large language models. Verification can be taught through explicit protocols: identify claims that require evidence, locate original sources, inspect whether citations exist, compare multiple references, test calculations where relevant, and record unresolved uncertainty. The precise routine should vary by discipline, but the principle is universal. A confident response is not equivalent to a supported academic claim. Educators should model verification in class by exposing flawed outputs and demonstrating how expert knowledge changes the evaluation. Library expertise can strengthen this work through source evaluation, database searching, and citation literacy. Assessment rubrics can reward the quality of verification rather than simply penalise errors. This gives students a positive reason to inspect AI output carefully. Verification also supports professional preparation because graduates will increasingly encounter automated recommendations in workplaces. The ability to establish whether a claim is trustworthy is therefore both an academic and occupational capability. Routine verification turns artificial intelligence into a stimulus for deeper information literacy rather than a replacement for evidence-based reasoning. Verification routines make responsibility observable by requiring students to show how generated claims were tested, supported, qualified, or rejected.

Universities should support verification through infrastructure and shared expectations, not assume that every educator will independently develop an effective approach. Institutional guidance can provide examples of common failure modes, recommended source-checking practices, privacy considerations, and discipline-specific case studies. Qian (2025) demonstrates the breadth of generative AI use across higher education, so verification support must be available wherever AI-generated knowledge enters learning. Educators also need practical ways to evaluate references and technical claims without creating unreasonable workload. Libraries, learning designers, and disciplinary experts can develop reusable verification resources that reduce duplication. Research on smart technology adoption shows that maintenance and system-related challenges continue after implementation (Yusof, Abdul Razak, Jamaludin, et al., 2025). The educational equivalent is continuous epistemic maintenance: claims need checking, guidance needs updating, and new system behaviours need to be understood. Students should be encouraged to disclose uncertainty rather than manufacture certainty when evidence is weak. This expectation is especially important because generative systems often present answers with a level of confidence unrelated to their reliability. A verification culture strengthens academic trust by making evidence traceable and judgement accountable. It also helps universities preserve a central scholarly norm: claims become credible through reasons and evidence, not through the authority or fluency of the technology that produced them. A university-wide verification culture strengthens scholarly trust while allowing each discipline to preserve its own standards of evidence and authority.

5.3 Authentic Assessment Architecture Protecting Meaningful Student Performance

Authentic assessment architecture should combine multiple forms of evidence so that student capability remains visible in an AI-rich environment. Instead of relying heavily on a single polished submission, courses can use staged work, oral explanation, supervised performance, reflective commentary, portfolios, peer critique, and applied projects. Xia et al. (2024) show that generative artificial intelligence is driving substantial reconsideration of assessment in higher education, while Bower et al. (2024) report educator support for changes that preserve meaningful evidence of learning. The architecture should be proportionate to the learning outcome. A foundational writing course may require protected independent writing; a senior professional module may permit extensive AI use but demand justification, verification, and oral defence. Assessment should also make process visible. Draft histories, decision logs, annotations, or short reflections can show how students used feedback and where artificial intelligence influenced the work. These elements are not intended as surveillance. They help educators interpret the final product and create opportunities for students to articulate their reasoning. Authentic assessment architecture therefore connects task design, evidence, feedback, and academic integrity. It becomes harder for generated output to substitute invisibly for learning because students must demonstrate competence across several moments and modes rather than through one artefact alone. Assessment architecture should provide enough varied evidence to show that graduates can perform independently as well as collaborate responsibly with artificial intelligence.

Assessment architecture should also communicate a coherent model of responsibility. Students need to know whether artificial intelligence is prohibited, optional, expected, or required within each task and which aspects of the work remain personally accountable. Disclosure requirements can be integrated into submission processes so that students explain what assistance was used and how outputs were verified. Bhullar et al. (2024) identify integrity as a major challenge in higher education, but clear design can reduce ambiguity before misconduct occurs. Active learning research also supports assessment that captures participation and application rather than passive reproduction (Kamarudin et al., 2025). Universities can strengthen consistency by developing design principles and examples rather than imposing one standard task format. Faculties can then adapt those principles to disciplinary needs. Periodic review is necessary because a task that provided reliable evidence one year may become vulnerable as AI capability changes. Assessment committees should therefore consider technological change as part of normal quality assurance. The strongest architecture does not attempt to make every assignment immune to artificial intelligence. It ensures that the overall programme contains sufficient evidence that graduates can reason independently, use tools responsibly, communicate decisions, and perform the capabilities associated with the award. This programme-level view is more defensible than reliance on isolated detection or prohibition. Programme-level assessment design is therefore more resilient than isolated attempts to make individual assignments resistant to every new technological capability.

5.4 Continuous Educator Development Building Sustainable Teaching Capability

Continuous educator development should be treated as part of academic quality rather than an optional technology initiative. Artificial intelligence changes too quickly for one-time training to remain sufficient, and educators need ongoing opportunities to update their knowledge, test new practices, and reconsider assessment. Ren and Wu (2025) identify teaching competencies as central

to successful integration, while Ellis et al. (2025) show that educators experience generative AI differently. Development should therefore combine common foundations with discipline-specific practice. Common foundations can include model limitations, privacy, bias, verification, disclosure, and assessment principles. Discipline-based activities can then address authentic tasks, standards of evidence, and professional expectations. Universities should provide spaces where staff can share both successful and unsuccessful experiments because failure often produces valuable professional learning. Mentoring and communities of practice can support colleagues who are less confident without framing them as resistant to innovation. Workload is equally important. Human-centred work design research indicates that professional capability depends on conditions that make effective performance possible (Abd Wahab & Yusof, 2020). Curriculum redesign, assessment redevelopment, and verification require time. Sustainable educator development therefore needs recognition within workload, promotion, and teaching quality systems rather than depending on voluntary effort alone. When professional learning is continuous, adequately resourced, and connected to evidence of student learning, technological change can strengthen teaching capability without displacing academic judgement or weakening institutional responsibility.

Professional development should increasingly focus on judgement rather than tool-specific techniques. Interfaces and products will change, but educators will continue to need the ability to evaluate educational purpose, verify generated knowledge, protect student agency, interpret ethical risk, and decide when automation should be limited. Chiu (2024) places AI literacy among the future capabilities required in higher education, and the same literacy is essential for educators. Scenario-based development can be particularly effective. Staff can work through cases involving fabricated citations, AI-assisted assessment, sensitive student data, unequal access, or automated feedback and discuss how competing values should be balanced. Organisational learning research emphasises the importance of reflection and knowledge exchange in sustaining innovation (Yusof, 2007). Universities can support this by maintaining living repositories of guidance and examples that evolve with practice. Development should also include leadership, professional services, and support staff because educator decisions are shaped by policy, infrastructure, and student services. The long-term capability is therefore institutional as well as individual. When professional learning becomes continuous, collaborative, and connected to real teaching problems, educators can respond to technological change without repeatedly starting from zero. This creates a more resilient teaching environment in which experimentation remains disciplined by academic purpose and evidence. Professional learning should therefore become a normal component of teaching quality, workload planning, and academic development rather than an occasional intervention.

5.5 Accountable Governance Enabling Responsible Artificial Intelligence Innovation

Accountable governance should provide clear principles that support responsible artificial intelligence use without attempting to prescribe every classroom decision. Core institutional expectations can address privacy, transparency, human oversight, academic integrity, accessibility, security, and verification. These principles should be stable enough to create trust but flexible enough to accommodate disciplinary differences and changing technology. Chiu (2024) demonstrates that generative artificial intelligence affects policy, pedagogy, assessment, and future capabilities simultaneously, making fragmented governance increasingly difficult to defend. Institutions should therefore identify who is responsible for policy interpretation, system approval, assessment guidance, and response to emerging risks. Students need accessible explanations of their

responsibilities, while educators need authoritative advice that can be applied to specific teaching contexts. Corporate governance research emphasises the value of ethical accountability and transparent decision making in sustainable organisational development (Yusof, Abdul Razak, Misnan, & Abdul Malik, 2026). Comparable principles apply to AI governance in universities. Institutions should also be transparent about their own use of artificial intelligence in advising, analytics, feedback, or administration. Accountability loses credibility when universities demand disclosure from students while obscuring automated practices of their own. Responsible governance is therefore reciprocal: it defines visible obligations for students, educators, administrators, and institutional decision makers whose choices influence academic learning, trust, and educational quality.

Governance should operate as a learning system rather than a static policy document. Universities can establish review cycles that draw on educator experience, student feedback, assessment outcomes, academic integrity cases, accessibility concerns, and developments in professional practice. This evidence can reveal where rules are too vague, too restrictive, or disconnected from classroom realities. Ellis et al. (2025) show substantial variation in educator experiences with generative artificial intelligence, reinforcing the importance of adaptive rather than uniform governance. Leadership capability is also essential. Yusof (2026) argues that digital and entrepreneurial leadership can support organisational performance when technological change is integrated with strategic capability. Academic leaders similarly need to balance innovation, risk, cost, workload, and educational standards without reducing governance to either enthusiasm or prohibition. Cross-functional committees can help by bringing together educators, learning designers, IT specialists, librarians, legal expertise, student representatives, and quality assurance staff. Their role should be to clarify principles and learn from implementation, not to centralise every pedagogical decision. Accountable governance ultimately creates the conditions in which educators can innovate with confidence because responsibilities are visible, support is available, and institutional values remain consistent as technology evolves. A learning-oriented governance model allows universities to revise weak rules while preserving stable commitments to academic standards, fairness, and human responsibility. Governance maturity is demonstrated when policy revision responds to evidence while preserving stable commitments to fairness, transparency, and academic responsibility.

6.0 CONCLUSION

Artificial intelligence is changing university teaching most significantly by altering the conditions under which educational judgement is exercised. Educators now work with systems capable of producing explanations, examples, feedback, code, summaries, images, and assessment responses at a scale that was previously impossible. These capabilities can improve responsiveness and expand instructional options, but they do not determine educational quality by themselves. Quality depends on whether artificial intelligence is connected to explicit learning purposes, subjected to disciplinary verification, and used in ways that preserve meaningful student effort. The strongest transformation is therefore pedagogical rather than technological. Teaching becomes more adaptive when educators can generate alternative support without lowering standards; assessment becomes more credible when reasoning and process are visible; and student capability becomes more future-relevant when learners can use artificial intelligence critically rather than depend on it passively. The continued

centrality of teacher judgement is not a sign that technology has failed to transform higher education. It is the condition that allows transformation to remain educationally legitimate.

Responsible integration also requires universities to move beyond isolated individual experimentation. Curriculum, assessment, professional development, academic integrity, infrastructure, and governance must reinforce one another if artificial intelligence is to become a sustainable educational resource. Educators need time and support to redesign real teaching practices, students need transparent expectations regarding acceptable assistance, and institutions need routines for reviewing the accuracy, fairness, accessibility, and consequences of AI-supported activity. Authentic assessment and verification are especially important because they preserve trust in what academic work represents. A graduate should be able to explain, justify, verify, and take responsibility for decisions even when computational assistance is available. This expectation aligns higher education with the realities of professional work while protecting the intellectual independence that distinguishes education from automated task completion. Governance should therefore enable informed experimentation within visible boundaries rather than alternate between unrestricted enthusiasm and blanket prohibition.

The long-term value of artificial intelligence in contemporary higher education will be measured by the quality of human capability it helps universities develop. Institutions that treat artificial intelligence primarily as a productivity tool may gain speed without improving learning, while institutions that treat it as a pedagogical challenge can redesign teaching around stronger evidence, deeper judgement, and more explicit responsibility. Educators remain central because they interpret context, establish standards, recognise learner needs, and decide when technological assistance advances or weakens educational purpose. Students remain central because learning ultimately requires them to think, evaluate, create, and accept responsibility for academic claims. Artificial intelligence can enrich these processes when it is integrated through purposeful curriculum design, credible assessment, continuous professional learning, verification, and accountable governance. Sustainable transformation therefore depends on preserving a clear hierarchy: educational purpose guides pedagogy, pedagogy guides technological use, and human judgement remains accountable for the consequences. That hierarchy offers higher education a defensible path for embracing artificial intelligence without allowing technological capability to redefine teaching on its own terms.

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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 competing interests or relationships exist that could reasonably be perceived as compromising the objectivity, academic integrity, or scholarly independence of the work.

3. Author Contribution Statement

Muhamad Fitri Radzuan: Conceptualization, development of the conceptual framework, literature synthesis, interpretation of scholarly evidence, preparation of the original manuscript, and critical revision.

Mohamad Nizam Adhaa Kamarudin: Literature review, development of conceptual arguments, analysis of educational and technological perspectives, validation of the scholarly content, and manuscript review.

Mohd Noor Afiq Ramlee: Literature synthesis, interpretation of higher education perspectives, critical evaluation of the conceptual arguments, manuscript editing, and refinement of the final work.

All authors contributed substantially to the intellectual development of the article, critically reviewed the manuscript, and approved the final version for publication.

4. Ethics Statement

This article is a conceptual study based exclusively on published scholarly literature and does not involve human participants, surveys, interviews, experiments, interventions, personal information, or primary data collection. Therefore, institutional ethical approval and informed consent were not required. The study was developed in accordance with established principles of academic integrity, responsible scholarship, accurate representation of scholarly sources, and appropriate acknowledgement of previous research. The authors assume responsibility for the interpretation, synthesis, and presentation of the literature used in developing the conceptual arguments presented in this article.

REFERENCES

- Abd Wahab, N. S., & Yusof, M. S. (2020). Ergonomic work design and its influence on healthcare professionals' well-being and performance. *The Asian Journal of Professional & Business Studies*, 1(2), 90–107. <https://doi.org/10.61688/ajpbs.v1i2.298>
- Abdullah, F. I., Yusof, M. S., & Abu Seman, S. (2020). Strategic warehouse management and supply chain performance in a changing business environment. *The Asian Journal of Professional & Business Studies*, 1(2), 73–89. <https://doi.org/10.61688/ajpbs.v1i2.155>
- Almasri, F. (2024). Exploring the impact of artificial intelligence in teaching and learning of science: A systematic review of empirical research. *Research in Science Education*, 54, 977–997. <https://doi.org/10.1007/s11165-024-10176-3>
- Baig, M. I., & Yadegaridehkordi, E. (2024). ChatGPT in the higher education: A systematic literature review and research challenges. *International Journal of Educational Research*, 127, 102411. <https://doi.org/10.1016/j.ijer.2024.102411>
- Bayaga, A. (2025). Leveraging AI-enhanced and emerging technologies for pedagogical innovations in higher education. *Education and Information Technologies*, 30, 1045–1072. <https://doi.org/10.1007/s10639-024-13122-y>
- Bhullar, P. S., Joshi, M., & Chugh, R. (2024). ChatGPT in higher education: A synthesis of the literature and a future research agenda. *Education and Information Technologies*, 29, 21501–21522. <https://doi.org/10.1007/s10639-024-12723-x>
- Blackie, M. A. L. (2024). ChatGPT is a game changer: Detection and eradication is not the way forward. *Teaching in Higher Education*, 29(4), 1109–1116. <https://doi.org/10.1080/13562517.2023.2300951>

- Bower, M., Torrington, J., Lai, J. W. M., Petocz, P., & Alfano, M. (2024). How should we change teaching and assessment in response to increasingly powerful generative artificial intelligence? Outcomes of the ChatGPT teacher survey. *Education and Information Technologies*, 29, 15403–15439. <https://doi.org/10.1007/s10639-023-12405-0>
- Chiu, T. K. F. (2024). Future research recommendations for transforming higher education with generative AI. *Computers and Education: Artificial Intelligence*, 6, 100197. <https://doi.org/10.1016/j.caeai.2023.100197>
- Ellis, R., Han, F., & Cook, H. (2025). Qualitatively different teacher experiences of teaching with generative artificial intelligence. *International Journal of Educational Technology in Higher Education*, 22, 33. <https://doi.org/10.1186/s41239-025-00532-2>
- Fischer, I., Sweeney, S., Lucas, M., & Gupta, N. (2024). Making sense of generative AI for assessments: Contrasting student claims and assessor evaluations. *The International Journal of Management Education*, 22(3), 101081. <https://doi.org/10.1016/j.ijme.2024.101081>
- Foung, D., Lin, L., & Chen, J. (2024). Reinventing assessments with ChatGPT and other online tools: Opportunities for GenAI-empowered assessment practices. *Computers and Education: Artificial Intelligence*, 6, 100250. <https://doi.org/10.1016/j.caeai.2024.100250>
- Ghani, M. Z., Radzuan, M. F., Uyob, S., Yusof, M. S., & Azlina, A. (2025). Employability of early childhood education graduates in Malaysia: Employer perspectives and market readiness. *The Asian Journal of Professional & Business Studies*, 6(2), 1–13.
- Kamarudin, M. A. I., Jaaffar, A. R., Yusof, M. S., Nawi, M. N. M., Sidek, S., Nuh, R., & Yusof, M. S. (2025). Entrepreneurship as a career path among university students: An action research on hands-on learning and follow-up approach in business through the Introduction to Entrepreneurship course. *Journal of Cultural Analysis and Social Change*, 10(2), 3284–3300. <https://doi.org/10.64753/jcasc.v10i2.2096>
- Kasneci, E., Seßler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., Gasser, U., Groh, G., Günemann, S., Hüllermeier, E., Krusche, S., Kutyniok, G., Michaeli, T., Nerdel, C., Pfeffer, J., Poquet, O., Sailer, M., Schmidt, A., Seidel, T., . . . Kasneci, G. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. *Learning and Individual Differences*, 103, 102274. <https://doi.org/10.1016/j.lindif.2023.102274>
- Krause, S., Panchal, B. H., & Ubhe, N. (2025). Evolution of learning: Assessing the transformative impact of generative AI on higher education. *Frontiers of Digital Education*, 2, 21. <https://doi.org/10.1007/s44366-025-0058-7>
- Otto, S., Ejsing-Duun, S., & Lindsay, E. (2025). Disruptive tensions and emerging practices: An exploratory inquiry into student perspectives on generative artificial intelligence in a problem-based learning environment. *Education and Information Technologies*, 30, 19111–19140. <https://doi.org/10.1007/s10639-025-13533-5>
- Qian, Y. (2025). Pedagogical applications of generative AI in higher education: A systematic review of the field. *TechTrends*, 69, 1105–1120. <https://doi.org/10.1007/s11528-025-01100-1>
- Ren, X., & Wu, M. L. (2025). Examining teaching competencies and challenges while integrating artificial intelligence in higher education. *TechTrends*, 69, 519–538. <https://doi.org/10.1007/s11528-025-01055-3>

- Tlili, A., Shehata, B., Adarkwah, M. A., Bozkurt, A., Hickey, D. T., Huang, R., & Agyemang, B. (2023). What if the devil is my guardian angel: ChatGPT as a case study of using chatbots in education. *Smart Learning Environments*, 10, 15. <https://doi.org/10.1186/s40561-023-00237-x>
- Wang, P., Jing, Y., & Shen, S. (2025). A systematic literature review on the application of generative artificial intelligence (GAI) in teaching within higher education: Instructional contexts, process, and strategies. *The Internet and Higher Education*, 65, 100996. <https://doi.org/10.1016/j.iheduc.2025.100996>
- Xia, Q., Weng, X., Ouyang, F., Lin, T. J., & Chiu, T. K. F. (2024). A scoping review on how generative artificial intelligence transforms assessment in higher education. *International Journal of Educational Technology in Higher Education*, 21, 40. <https://doi.org/10.1186/s41239-024-00468-z>
- Yusof, M. S. (2025a). Technology adoption in small and medium enterprises and its impact on business growth, innovation, and digital sustainability. *International Journal of Advanced Research in Economics and Finance*, 7(3), 84–100. <https://doi.org/10.55057/ijaref.2025.7.3.7>
- Yusof, M. S. (2025b). The influence of digital adoption on the growth and resilience of rural agro-food entrepreneurs. *International Journal of Business and Technology Management*, 7(6), 316–334. <https://doi.org/10.55057/ijbtm.2025.7.6.27>
- Yusof, M. S. (2026). Integrating digital and entrepreneurial leadership: A framework for SME performance in emerging economies. *Jurnal Evolusi*, 7(1), 62–77. <https://doi.org/10.61688/jev.v7i1.568>
- Yusof, M. S., & Abd Wahab, N. S. (2021). Balancing technology and ethics in the transformation of modern hospital healthcare. *The Asian Journal of Professional & Business Studies*, 2(1), 16–34. <https://doi.org/10.61688/ajpbs.v2i1.146>
- Yusof, M. S., Abdul Razak, N., Jamaludin, A., Abdulloh, N. N., Ahmad, A., & Mat Zin, Z. (2025a). Integrating smart technologies in warehouse management to overcome system maintenance and security issues. *International Journal of Environmental Sciences*, 11(20s), 533–543.
- Yusof, M. S., Abdul Razak, N., Misnan, N., & Abdul Malik, H. K. (2026). Corporate governance and ethical accountability in sustainable organizational development. *Jurnal Evolusi*, 7(1), 14–31. <https://doi.org/10.61688/jev.v7i1.564>
- Yusof, M. S., Fauzi, N., Mat Yusop, Z., Mohamad Yunus, M. H. S., & Wahid, A. (2025b). Advanced approaches to enhancing picking and packing efficiency through smart automation and optimization. *International Journal of Business and Technology Management*, 7(2), 14–25. <https://doi.org/10.55057/ijbtm.2025.7.2.3>
- Yusof, M. S., Kamarudin, M. A. I., Wahid, A., & Osman, M. F. (2025c). The impact of digital transformation: An empirical analysis on the stability of agro-food SMEs. *International Journal of Business and Technology Management*, 7(6), 287–301. <https://doi.org/10.55057/ijbtm.2025.7.6.24>
- Yusof, M. S., Othman, N., Zaini, A. F. A., Manan, D. I. A., & Jali, M. N. (2025d). Digital mobility and learning behavior within the humanities education perspective among university students using Grab e-hailing services. *Veredas do Direito*, 22(6), e224040.

- Yusof, M. S., Razak, N. A., & Fauzi, N. (2025e). Empowering small and medium enterprises in Terengganu through technological learning and innovation for economic growth. *Veredas do Direito*, 22(7), e224108.
- Yusof, M. S., Salleh, M. N., & Zahari, F. M. (2020). The relationship between information technology capability and new product development success: A conceptual framework. *International Journal of Business and Technology Management*, 2(1), 98–112.
- Zaini, A. F. B. A., Yusof, M. S. B., Jamaludin, A., Yunus, M. H. S. M., & Hashim, F. (2026). Consumer review perception and its impact on Generation Z online spending behaviour in modern digital commerce. *Veredas do Direito*, 23(1), e234304.
- Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education: Where are the educators? *International Journal of Educational Technology in Higher Education*, 16, 39. <https://doi.org/10.1186/s41239-019-0171-0>