Enhancing Academic Productivity Through Artificial Intelligence: The Mediating Role of AI Literacy Among Malaysian University Students

Nur Syaahidah Mohamad[1*], Ramizatunnisah Jais[1], Nur Shafini Mohd Said[1], Siti Rapidah Omar Ali[1], Farah Ahlami Mansor[2]

[1]Faculty of Business and Management, Universiti Teknologi MARA (UiTM) Terengganu, Dungun Campus, 23000 Dungun, Terengganu, Malaysia

[2]Faculty of Business and Management, Universiti Teknologi MARA (UiTM) Kelantan, Machang Campus, 18500 Machang, Kelantan, Malaysia

***Corresponding Author**

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ABSTRACT

The swift adoption of generative artificial intelligence (AI) in higher education has transformed student learning, presenting unparalleled opportunities for automated drafting, syntactic polish, and literature synthesis, while introducing profound vulnerabilities regarding algorithmic hallucinations, cognitive offloading, and threats to academic integrity. This conceptual paper addresses critical gaps in technology acceptance literature by proposing an integrative model that positions AI literacy as a pivotal cognitive and evaluative mediating mechanism between multidimensional AI usage and academic productivity. Grounded in the Technology Acceptance Model (TAM), Cognitive Load Theory (CLT), and contemporary AI literacy frameworks, the paper decouples raw technological interaction from substantive educational attainment. We demonstrate that while system usage directly enhances operational task completion velocity, substantive scholarly productivity—defined by analytical depth, critical rigor, and epistemic accuracy—depends upon multidimensional AI literacy (technical understanding, effective prompting, critical output evaluation, and ethical reflexivity). Four refined theoretical propositions are formulated, accounting for competing explanatory mediators (such as academic motivation, prior academic achievement, and institutional support) and contextual moderating boundaries (academic discipline, year of study, and premium tool access). To bridge conceptual theory and empirical practice, operational definitions and a comprehensive measurement item pool are provided alongside an illustrative dual-scenario analysis. Finally, specific contextual considerations for Malaysian higher education, an expanded discussion of germane load reduction hazards, a structured limitations section, and a rigorous time-lagged PLS-SEM empirical validation blueprint are detailed for future researchers, educators, and university administrators.

Keywords: Artificial Intelligence, Generative AI, AI Literacy, Academic Productivity, Cognitive Load Theory, Technology Acceptance Model, Higher Education, Malaysian University Students

INTRODUCTION

The rapid integration of artificial intelligence (AI), particularly generative pre-trained transformers and large language models (LLMs), has precipitated a paradigm shift across global tertiary education (Cotton et al., 2024; Dwivedi et al., 2023). Within the Malaysian higher education sector, undergraduate and postgraduate students routinely deploy conversational and analytical AI tools—such as ChatGPT, Claude, Microsoft Copilot, and Gemini—into their daily academic routines. These systems are leveraged across a spectrum of scholarly tasks, including exploratory ideation, conceptual clarification, foreign language translation, code debugging, and syntactical refinement of research assignments (Kasneci et al., 2023; Sullivan et al., 2023).

These technologies present compelling procedural efficiencies, enabling students to circumvent mundane cognitive bottlenecks and accelerate written communication. However, generative tools simultaneously expose students to systemic vulnerabilities: algorithmic hallucinations, fabricated academic citations, embedded socio-cultural biases, and misleading epistemic confidence (Alkaissi & McFarlane, 2023; UNESCO, 2023).

The paramount pedagogical challenge facing contemporary universities is not managing technological access but understanding how students interact with these systems and whether such interaction fosters authentic cognitive mastery or encourages superficial task compliance (Lodge et al., 2023). Extant scholarship underscores that increased frequency or duration of AI usage does not naturally result in superior academic performance (Zawacki-Richter et al., 2019; Baidoo-Anu & Ansah, 2023). When AI is utilized as a collaborative metacognitive partner—scaffolding ideation and prompting self-directed critique—intellectual productivity is magnified. Conversely, when technological deployment devolves into uncritical cognitive offloading, students incur significant learning losses, intellectual dependency, and accidental violations of institutional academic integrity (Risko & Gilbert, 2016; Perkins, 2023). Consequently, a learner's evaluative competence acts as the primary cognitive gatekeeper determining whether system adoption translates into authentic scholarly rigor or superficial text assembly.

To conceptualize this evaluative capability, the construct of AI literacy has emerged as an essential scholarly framework (Long & Magerko, 2020; Ng et al., 2021). Going beyond operational computer literacy, AI literacy entails a nuanced nexus of higher-order competencies: understanding foundational algorithmic principles and constraints, formulating contextualized prompts, critically appraising algorithmic accuracy against verified domain literature, and navigating complex ethical dilemmas surrounding authorship, intellectual property, and data privacy (Kong et al., 2024; Laupichler et al., 2022). Without these evaluative proficiencies, students lack the cognitive mechanisms necessary to detect subtle machine errors or resist unreflective text reproduction.

This paper presents a conceptual model examining the mediating role of AI literacy between multidimensional AI usage and academic productivity among Malaysian university students. This revised and expanded study contributes to the literature in four distinct ways:

- **Decoupling Usage from Scholarly Attainment:** It distinguishes routine tool interaction from evaluative user competence, demonstrating that system adoption metrics cannot serve as a valid proxy for pedagogical attainment.

- **Theoretical Integration of TAM and Cognitive Load Theory:** By synthesizing the Technology Acceptance Model (Davis, 1989) with Cognitive Load Theory (Sweller, 1988, 2011), the study explains how AI literacy functions as a cognitive mediator, clarifying the risks of excessive cognitive offloading that threaten germane learning schemas.

- **Addressing Alternative Mechanisms and Boundary Conditions:** It contextualizes the usage–productivity dynamic by examining competing explanatory mediators (prior ability, motivation, and institutional scaffolding) alongside key moderators such as academic discipline, study level, and institutional resource tiers.

- **Empirical Operationalization and Contextual Guidance:** It provides a concrete measurement blueprint (complete with construct indicators), a real-world task scenario, and tailored policy guidance aligned with the Malaysian Ministry of Higher Education's digital transformation roadmaps.

LITERATURE REVIEW

Artificial Intelligence Usage in Higher Education

In this framework, AI usage is defined as a student's active, goal-directed behavioral engagement with AI-driven digital systems to execute academic responsibilities (Kasneci et al., 2023). Far from being a monolithic activity, AI usage spans varying levels of cognitive complexity: from superficial operational tasks (e.g., proofreading and structural formatting) to complex evaluative tasks (e.g., conceptual co-reasoning, statistical

code generation, and interdisciplinary thematic synthesis) (Dwivedi et al., 2023). Quantitative metrics that merely record daily log-ins or weekly usage hours fail to capture this qualitative diversity. Without considering interactional depth and prompting sophistication, raw frequency metrics obscure whether AI serves as an authentic cognitive scaffold or as a substitute for critical thought (Lodge et al., 2023; Cotton et al., 2024).

The Technology Acceptance Model (TAM) and Post-Adoption Realities

The Technology Acceptance Model (TAM) posits that user adoption is governed by Perceived Usefulness (PU) and Perceived Ease of Use (PEOU), which shape behavioral intention and actual usage (Davis, 1989; Venkatesh & Bala, 2008). In tertiary institutions, generative AI tools enjoy unprecedented adoption velocity because students perceive them as exceptionally capable of accelerating assignment completion while requiring minimal technical training. Nevertheless, classical TAM exhibits significant explanatory limitations in educational settings: it models the adoption decision but remains agnostic toward the qualitative output, factual rigor, and ethical legitimacy of post-adoption behavior (Venkatesh et al., 2003; Ng et al., 2021). While TAM successfully explains *why* university students adopt generative tools, it fails to explain *what pedagogical outcomes* arise from that usage. Introducing AI literacy resolves this structural limitation by positioning evaluative competency as a vital post-adoption determinant of academic success.

Academic Productivity: Operational Efficiency versus Scholarly Rigor

Past educational technology literature has frequently operationalized academic productivity as a single composite index of task completion speed and student GPA. This paper argues that such an aggregation is conceptually flawed when studying generative technologies. Academic productivity must be decoupled into two distinct, interdependent dimensions:

- **Operational Efficiency:** Procedural velocity, time optimization, task acceleration, and reduction of administrative or formatting friction.

- **Scholarly Rigor:** Conceptual depth, critical argumentation, factual and citation accuracy, contextual originality, and adherence to academic integrity frameworks.

Accelerated text generation without scholarly rigor yields zero academic value; in fact, submitting plausible sounding but hallucinated content incurs severe academic penalties (Alkaissi & McFarlane, 2023; Perkins, 2023). Consequently, genuine scholarly productivity requires the simultaneous maintenance of procedural efficiency and intellectual rigor.

AI Literacy: Dimensions, Competencies, and Cognitive Offloading

AI literacy is defined as the integrated set of cognitive, operational, and ethical competencies required to productively interact with, evaluate, and govern artificial intelligence systems (Long & Magerko, 2020;

Knowing and Understanding AI: Grasping machine learning fundamentals, stochastic text generation mechanisms, algorithmic constraints, and probabilistic uncertainty.

1. **Using and Applying AI:** Designing iteratively refined, contextualized prompts and deploying domain-specific AI tools for structured problem-solving.
2. **Evaluating and Creating with AI:** Systematically auditing machine outputs, cross-referencing generated assertions against empirical literature, detecting algorithmic bias, and synthesizing AI outputs with original human analysis.
3. **Ethical and Reflexive Engagement:** Understanding data security, copyright governance, intellectual transparency, citation honesty, and university disclosure regulations.

Without these dimensions, students are vulnerable to uncritical *cognitive offloading*—the physical or digital outsourcing of cognitive tasks to external artifacts (Risko & Gilbert, 2016). While offloading routine

calculations or clerical formatting is cognitively adaptive, offloading primary synthesis, evaluation, and argumentation impairs deep schema formation (Lodge et al., 2023).

Theoretical Synthesis: Cognitive Load Theory (CLT) and the Germane Load Paradox

Cognitive Load Theory (CLT) provides the cognitive architecture explaining how AI literacy transforms raw tool engagement into academic achievement (Sweller, 1988, 2011; Paas & van Merriënboer, 2020). CLT classifies cognitive load into three types:

- **Intrinsic Load:** The inherent cognitive difficulty of the academic topic.
- **Extraneous Load:** Mental effort generated by task presentation, structural mechanics, or surface-level language execution.
- **Germane Load:** Mental resources dedicated to schema construction, conceptual synthesis, critical comparison, and deep understanding.

Working memory is strictly limited in capacity (Sweller, 1988). When used constructively, generative AI automates syntactical organization, brainstorming, and literature retrieval, thereby reducing *extraneous load*. This reduction frees working memory, which can then be redirected toward *germane load*—enabling students to engage in rigorous evaluation, conceptual analysis, and creative synthesis.

The Germane Load Paradox: However, CLT reveals an important risk when students interact with high-capability AI models. If students utilize AI to generate entire arguments, outlines, and analytical conclusions, they inadvertently offload the very mental effort that constitutes germane load. Even highly AI-literate students face an epistemic temptation: because the AI generates coherent, well-structured prose effortlessly, the student's working memory experiences negligible struggle, leading to the illusion of learning without actual schema encoding (Sweller, 2011; Lodge et al., 2023). Therefore, high AI literacy is not merely a set of technical prompt skills; it must function as a conscious metacognitive regulator that preserves germane load by intentionally maintaining human analytical effort during the learning process.

Conceptual Framework, Propositions and Alternative Explanations

PROPOSED CONCEPTUAL FRAMEWORK

The proposed framework posits that multidimensional AI usage influences academic productivity through two parallel routes: a direct path toward operational efficiency and an indirect path toward scholarly rigor mediated by AI literacy. Furthermore, the framework recognizes that this core dynamic is situated among competing mediators and bounded by specific individual and contextual moderators.

Pathway Type	Source Construct	Intervening / Outcome Construct	Theoretical Rationale & Cognitive Mechanism
Direct Pathway	AI Usage	Operational Efficiency	Procedural automation of syntax correction, formatting, and scheduling directly compresses task completion duration.
First Stage Indirect	AI Usage	AI Literacy	Iterative, hands-on tool engagement provides experiential discovery, trial-and-error prompt refinement, and error-pattern recognition.
Second Stage Indirect	AI Literacy	Academic Productivity (Scholarly Rigor)	Evaluative auditing, hallucination detection, contextual verification, and ethical adherence directly drive research depth and rigor.
Indirect Mediation	AI Usage → AI Literacy	Scholarly Rigor	Essential / Full Mediation: Raw usage alone exhibits a non-significant or negative relationship with scholarly rigor; AI literacy is the indispensable mechanism required to realize scholarly quality.

THEORETICAL PROPOSITIONS

Proposition 1 (P1): *AI usage is positively associated with operational academic efficiency among Malaysian university students.*

Rationale: Routine interaction with generative language tools allows students to offload procedural mechanics, such as draft structuring, grammar refinement, and document formatting. This reduces extraneous cognitive load and accelerates assignment delivery times, regardless of the underlying intellectual depth of the submission.

Proposition 2 (P2): AI usage is positively associated with student AI literacy, contingent upon iterative, experiential engagement.

Rationale: Competence is acquired through deliberate practice. As students interact across varied academic tasks (e.g., querying concepts, debugging code, drafting outlines), they experience model limitations firsthand,

developing mental models of algorithmic behaviors, prompt engineering strategies, and hallucination risks over time (Kong et al., 2024).

Proposition 3 (P3): AI literacy is positively associated with overall academic productivity, with its strongest impact on scholarly rigor and accuracy.

Rationale: Students possessing advanced AI literacy can formulate nuanced prompts, cross-examine synthetic claims against empirical academic databases, mitigate algorithmic bias, and comply with institutional academic

ntegrity mandates. This capability ensures that the final scholarly submission demonstrates rigorous conceptual synthesis rather than unverified machine output.

Proposition 4 (P4): AI literacy partially mediates the relationship between AI usage and operational efficiency, but fully (essentially) mediates the relationship between AI usage and scholarly rigor.

Theoretical Defense against Competing Mediation Models: While raw technological usage is sufficient to accelerate procedural speed (yielding partial mediation for operational efficiency), empirical evidence demonstrates that tool usage alone does not improve—and frequently degrades—critical inquiry, conceptual

depth, and empirical validity (Cotton et al., 2024; Perkins, 2023). When entered into a competitive structural model, the direct path from raw AI usage to scholarly rigor is expected to be statistically non-significant or

Alternative Explanations: Competing Mediators

To avoid theoretical misspecification, our framework explicitly accounts for three established competing mechanisms that explain academic productivity gains:

1. **Prior Academic Ability (Baseline GPA):** High-achieving students possess robust self-regulated learning skills and pre-existing cognitive schemas (Zimmerman, 2002), allowing them to extract higher value from AI tools regardless of formal AI training.

2. **Academic Motivation and Epistemic Curiosity:** Students driven by intrinsic mastery goals utilize AI for intellectual exploration, whereas extrinsically performance-avoidant students use AI for unauthorized shortcutting (Ryan & Deci, 2000).

3. **Perceived Institutional and Pedagogical Support:** Clear institutional guidelines, instructional scaffolding, and supportive lecturer attitudes directly facilitate effective technology utilization (Venkatesh & Bala, 2008).

Any empirical test of the AI literacy mediation pathway must include these three factors as statistical controls or parallel mediating variables to isolate the unique variance explained by AI literacy.

Boundary Conditions: Moderating Variables

The strength of the relationships among AI usage, AI literacy, and productivity is moderated by key individual and environmental boundary conditions:

- **Academic Discipline (STEM vs. Social Sciences / Humanities):** In STEM and programming domains, AI outputs are frequently deterministic and immediately testable (e.g., verifying if code compiles or mathematical solutions solve correctly), accelerating literacy acquisition. In Social Sciences and Humanities, AI outputs are nuanced, rhetoric-heavy, and prone to plausible hallucinations, requiring higher evaluative literacy to avoid errors.

- **Year of Study (Undergraduate vs. Postgraduate):** Senior and postgraduate students possess established domain schemas, enabling them to evaluate AI claims critically. Junior undergraduates, who are still developing foundational domain knowledge, are more vulnerable to uncritical acceptance of AI-generated text.

- **Tier of AI Access (Free-Tier vs. Premium Frontier Models):** Premium models demonstrate superior reasoning, broader context windows, and fewer hallucinations compared to free-tier, parameter-capped architectures. Access disparities may directly moderate the relationship between usage and operational productivity.

Operational Definitions, Measurement Guidance, And Illustrative Task Scenario

AI Usage (AIU)				
Frequency, diversity, and depth of task-directed behavioral engagement with generative AI tools for academic work.				
Adapted from Davis (1989); Venkatesh & Bala (2008); Kasneci et al. (2023)				
Multi-faceted capability to understand, apply, evaluate, and ethically govern generative AI systems in academic tasks.				
AI Literacy (AIL)				
Multi-faceted capability to understand, apply, evaluate, and ethically govern generative AI systems in academic tasks.				
Adapted from Ng et al. (2021); Long & Magerko (2020); Laupichler et al. (2022)				
AI Literacy (AIL)				
Multi-faceted capability to understand, apply, evaluate, and ethically govern generative AI				

systems in academic tasks.				
Adapted from Ng et al. (2021); Long & Magerko (2020); Laupichler et al. (2022)				
AI Literacy (AIL)				
Multi-faceted capability to understand, apply, evaluate, and ethically govern generative AI systems in academic tasks.				
Adapted from Ng et al. (2021); Long & Magerko (2020); Laupichler et al. (2022)				
Dual-dimensional attainment comprising operational workflow efficiency and rigorous scholarly achievement.				
Academic Productivity (AP)				
Dual-dimensional attainment comprising operational workflow efficiency and rigorous scholarly achievement.				
Adapted from Davis (1989); Cotton et al. (2024); Dwivedi et al. (2023)				
Operationalization and Measurement Item Pool To facilitate rigorous empirical validation through Structural Equation Modelling (SEM), Table 2 presents operational definitions alongside adapted multi-item measurement scales evaluated on a 7-point Likert scale (1 = Strongly Disagree, 7 = Strongly Agree).Construct & Operational Definition	Dimension / Sub-Facet	Sample Measurement Items	Source Adaptation	
AI Usage (AIU) Frequency, diversity, and depth of task-directed behavioral engagement with generative AI tools for academic work.	Procedural & Syntactic Usage	• AIU1: I regularly use generative AI tools to assist in formatting and structuring my academic assignments. • AIU2: I use AI tools to refine the grammar, syntax, and readability of my written academic work.	Adapted from Davis (1989); Venkatesh & Bala (2008); Kasneci et al. (2023)	
	Conceptual &	• AIU3: I utilize AI		

	Analytical Usage	systems to brainstorm ideas and explore unfamiliar academic concepts. • AIU4: I deploy AI tools to assist in analyzing data, debugging code, or summarizing academic literature.		
AI Literacy (AIL)	Understanding & Technical Literacy (UTL)	• AIL_U1: I understand how generative AI models process data to produce responses. • AIL_U2: I am aware of the technical limitations of AI, including its tendency to generate hallucinations and false citations.	Adapted from Ng et al. (2021); Long & Magerko (2020); Laupichler et al. (2022)	
	Prompt Engineering & Application (PEA)	• AIL_P1: I can construct detailed, contextual prompts to elicit precise and relevant academic information from AI. • AIL_P2: I iteratively adjust my prompts based on the quality and accuracy of the AI's preliminary output.		
Critical Evaluation & Verification (CEV)	• AIL_E1: I systematically cross-check claims, data, and references generated by AI against peer-reviewed literature. • AIL_E2: I critically analyze AI-generated arguments to detect underlying biases, inconsistencies, or gaps in logic.			
Ethical & Transparent Use (ETU)	• AIL_T1: I adhere to			

	institutional ethical guidelines regarding the disclosure and transparent reporting of AI tool usage. • AIL_T2: I ensure that using AI tools does not compromise my academic integrity or lead to uncredited plagiarism.			
Academic Productivity (AP)	Operational Efficiency (AP_OE)	• AP_E1: Integrating AI into my workflow allows me to complete assignments significantly faster. • AP_E2: AI tools help me manage my academic workload more efficiently and meet challenging deadlines.		Adapted from Davis (1989); Cotton et al. (2024); Dwivedi et al. (2023)
Scholarly Rigor & Depth (AP_SR)	• AP_R1: My interaction with AI enhances the analytical depth and conceptual clarity of my research submissions. • AP_R2: Incorporating AI helps me produce work that meets rigorous standards of originality, evidence verification, and scholarly critique.			

Illustrative Scenario: Tracing the Dual Pathways in a Literature Review Task

To demonstrate how the mediation pathway operates in everyday university tasks, consider a real-world scenario of two undergraduate business students at a Malaysian university tasked with conducting a 3,000-word critical literature review on "Sustainable Supply Chain Management."

Student A: High AI Usage, Low AI Literacy (The Direct Path Failure)

Student A submits a broad, single prompt: *"Write a 3,000-word literature review on sustainable supply chain management with 20 academic references."* Within moments, the AI generates a coherent, grammatically polished document. Student A experiences high **operational efficiency**—the drafting task was completed in under fifteen minutes. However, because Student A lacks technical understanding and critical evaluation competencies, they fail to recognize that six of the cited citations are non-existent AI hallucinations, while the theoretical framework confuses classical sustainability models with unverified industry buzzwords. Student A uncritically offloaded all cognitive effort, bypassing the working memory engagement necessary to build

subject-matter schemas. The outcome: severe procedural speed, but zero **scholarly rigor**, resulting in academic integrity penalties and failed learning objectives.

Student B: High AI Usage, High AI Literacy (The Fully Mediated Pathway)

Student B uses AI across iterative steps, applying advanced AI literacy. First, Student B uses AI to offload extraneous cognitive load by requesting an outline of current debates in sustainable supply chains. Recognizing the risk of hallucinations, Student B does not accept generated citations; instead, they retrieve primary empirical papers from Scopus and Web of Science. Student B then uses AI as a cognitive peer by inputting the empirical findings and prompting: *"Identify theoretical disagreements between Author X and Author Y regarding carbon-neutral supply chains, highlighting potential methodological limitations."* Student B evaluates the machine's synthesis against the primary texts, edits out biases, injects local Malaysian industry contexts, and appends a transparent AI disclosure statement. Student B achieves high **operational efficiency** (saving hours of initial structuring) while simultaneously maximizing **scholarly rigor** (achieving deep theoretical comparison and verified accuracy). AI literacy mediated this successful outcome by directing mental capacity toward active germane schema acquisition.

Contextual Dynamics In Malaysian Higher Education

Examining AI integration within Malaysian higher education requires an understanding of distinct national socio-technical and cultural factors:

1. **Digital Transformation vs. Subscription Disparities:** Under national blueprints such as the Malaysia Education Blueprint (Higher Education) and the National Artificial Intelligence Roadmap (AI4Malaysia), the Ministry of Higher Education (MOHE) has prioritized institutional digitalization. However, notable resource disparities persist between research-intensive universities (e.g., Universiti Malaya, Universiti Teknologi MARA) and smaller regional or private colleges. Students at well-funded institutions frequently receive subsidized access to enterprise-grade AI models, whereas students in under-resourced settings rely on free-tier, parameter-capped engines prone to higher hallucination rates. This digital divide impacts the ease with which students acquire advanced AI literacy.
2. **ESL Language Scaffolding and Linguistic Parity:** In Malaysia's bilingual higher education environment, English functions as the primary medium of instruction across business, engineering, and postgraduate studies. For students from English as a Second Language (ESL) backgrounds, generative AI serves as an essential cognitive and linguistic scaffold. When mediated by high AI literacy, generative tools alleviate foreign language anxiety, enabling students to articulate sophisticated research ideas without grammatical bottlenecks. However, when literacy is deficient, students often adopt unidiomatic or syntactically inflated prose that obscures their authentic analytical voice.
3. **Institutional Policy Heterogeneity and Ethical Governance:** Malaysian tertiary institutions exhibit varied regulatory stances toward GenAI. While several leading universities have issued forward-thinking guidelines encouraging AI co-piloting with mandatory transparent attribution, others have instituted punitive honor-code bans. Institutional policy ambiguity pushes AI usage underground, discouraging open dialogue between students and faculty and preventing the formal pedagogical training necessary to cultivate ethical AI literacy.

Practical and Pedagogical Implications For Higher Education

Universities must move beyond reactive prohibition and establish proactive, institution-wide enablement frameworks:

- **Curriculum-Integrated AI Literacy Interventions:** AI literacy instruction should not be relegated to optional extracurricular seminars. Institutions must embed credit-bearing literacy modules directly within core research methodology and academic writing curricula. Training must emphasize iterative prompt engineering, systematic citation verification on indexed scholarly databases, bias audits, and institutional disclosure ethics.

- **Transition to Process-Oriented Assessment:** Traditional text-centric evaluations (e.g., take-home essays, unproctored literature summaries) cannot reliably assess genuine student capability in the generative AI era. Educators should transition toward process-oriented evaluation designs, including:
    - Mandatory submission of iterative prompt audit trails and intermediate drafts.
    - Annotated reflection reports comparing original human writing with AI-suggested revisions.
    - In-person oral defenses, conceptual viva voces, and collaborative classroom synthesis tasks that make individual student metacognition visible.
- **Institutional Policy Transparency and Ethical Disclosure:** Universities should establish clear, unified AI governance frameworks. Guidelines should outline acceptable use thresholds, provide standardized AI acknowledgement templates (e.g., documenting model version, prompt architecture, and nature of editorial assistance), and reassure students that ethical, transparent AI co-reasoning is welcomed.

Methodological Blueprint For Future Empirical Validation

To rigorously evaluate the proposed conceptual model, future empirical studies should execute the following methodological blueprint:

- **Sampling Design and Power Requirements:** A stratified multi-stage sampling technique should be deployed across diverse public and private universities in Malaysia, ensuring proportional representation across disciplines (STEM, Social Sciences, Business, Humanities) and academic levels. A statistical power analysis conducted via G*Power indicates that to test a structural model comprising 4 primary constructs, 8 sub-dimensions, and 3 control variables at an alpha level of $\alpha = 0.05$ and power of 0.95 with a medium effect size ($f^2 = 0.15$), a minimum sample size of $N = 280$ is required. Researchers should target $N \geq 400$ to accommodate non-response and sub-group multi-group analysis (MGA).
- **Time-Lagged (Two-Wave) Data Collection Design:** Cross-sectional designs are fundamentally ill-suited for examining mediation, as collecting predictors, mediators, and outcomes concurrently inflates common method variance and obscures temporal causality (Podsakoff et al., 2012). Researchers should implement a two-wave time-lagged design:
    - **Time 1 (T1):** Measure exogenous predictors (AI Usage frequency and task types), TAM antecedents (PU, PEOU), and control variables (prior GPA, motivation).
    - **Time 2 (T2, 4–6 weeks later):** Measure the mediating construct (AI Literacy dimensions) and end-stage academic outcomes (Operational Efficiency and Scholarly Rigor).
- **Analytical Framework: PLS-SEM:** Partial Least Squares Structural Equation Modelling (PLS-SEM) via SmartPLS 4 is recommended due to the presence of higher-order constructs (AI Literacy and Academic Productivity) and complex mediation pathways (Hair et al., 2022). Evaluation should follow a two-step analytical protocol:
    - **Measurement Model Evaluation:** Establish indicator reliability (outer loadings > 0.708), construct internal consistency (Cronbach's alpha > 0.70, Composite Reliability > 0.80), convergent validity (Average Variance Extracted, AVE > 0.50), and discriminant validity via the Heterotrait-Monotrait ratio of correlations (HTMT < 0.85).
    - **Structural Model Evaluation:** Assess collinearity (Variance Inflation Factors, VIF < 3.3), coefficient of determination (R^2), effect sizes (f^2), and predictive relevance ($Q^2_{predict}$). Mediation significance for P4 must be validated using bootstrapping with 10,000 resamples to generate 95% bias-corrected confidence intervals.

- **Mitigating Common Method Variance (CMV):** Procedural remedies must include psychological separation of measurement items, explicit guarantees of participant confidentiality, and counterbalanced item presentation. Statistically, CMV should be tested using Harman's single-factor test and the comprehensive full-collinearity assessment approach (Kock, 2015), ensuring all factor VIFs remain below the 3.3 threshold.

Limitations

While this paper presents an integrative theoretical framework, several conceptual and methodological limitations must be acknowledged:

1. **Absence of Primary Empirical Validation:** As a conceptual paper, the proposed propositions and structural pathways have not yet undergone primary empirical testing. Consequently, the theorized relationships remain formal hypotheses that require rigorous statistical confirmation.

2. **Self-Report Measurement Subjectivity:** The proposed measurement scales rely upon student self-reports regarding usage frequency, perceived literacy, and academic productivity. Self-report metrics in technology adoption literature are prone to social desirability bias and the Dunning-Kruger effect, wherein students with lower competence may overestimate their AI evaluative literacy. Future studies should complement survey scales with objective skill assessments or experimental prompt-testing tasks.

3. **Rapidly Evolving Technological Landscape:** The capabilities of frontier generative AI systems change quickly. As models incorporate advanced multi-step reasoning, integrated code interpreters, and automated fact-checking, the specific nature of user cognitive load and prompt interaction may evolve, necessitating ongoing reassessment of the AI literacy construct.

CONCLUSION

The growing presence of generative AI in tertiary education marks an irreversible shift in scholarly practice. Yet this conceptual study highlights a central educational reality: raw system usage alone is insufficient to elevate scholarly productivity. By synthesizing the Technology Acceptance Model with Cognitive Load Theory, this paper establishes that AI literacy serves as the decisive cognitive and evaluative mediator that transforms technological interaction into authentic academic achievement. Grounded in the socio-educational realities of Malaysian universities, our framework provides a theoretical foundation, empirical operationalization, and actionable institutional guidance to help students, educators, and policy makers harness AI as an intellectual scaffold while preserving the critical rigor of higher learning.

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