The Efficiency Paradox: Modeling Student Engagement and AI Dependence on STEM Productivity in a Philippine State University

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***Abstract*—The integration of Generative Artificial Intelligence (GenAI) in Science, Technology, Engineering, and Mathematics (STEM) education has created an "Efficiency Paradox", where students may rely on algorithms not out of incompetence, but to manage increasing academic workloads. Distinct from previous research that predominantly examines AI through the lens of academic integrity or general acceptance, this study investigates the psychological mechanisms linking student engagement to AI dependence and output productivity. This study empirically modeled the dual pathways of student engagement and AI dependence on output productivity. Employing a descriptive-predictive correlational design, data were collected from 915 undergraduate STEM students at a state university in the southern Philippines. Partial Least Squares Structural Equation Modeling (PLS-SEM) and Importance-Performance Map Analysis (IPMA) were utilized to analyze the relationships between digital literacy, perceived usefulness, self-efficacy, motivation, time management, AI dependence, and productivity. The structural model explained 75.2% of the variance in productivity ($R^2 = 0.752$). The findings revealed that Time Management was the single strongest driver of both AI Dependence ($\beta = 0.409$) and Productivity ($\beta = 0.605$), suggesting that dependence is often a strategic adaptation for efficiency. Conversely, Intrinsic Motivation acted as a buffer, significantly reducing reliance on AI tools ($\beta = -0.460$). IPMA results highlight that while students possess high digital literacy, it has low impact on productivity compared to regulatory skills. The study concludes that higher education policy at the institutional level should shift focus from basic AI literacy to fostering self-regulation and time management to prevent pathological dependence.**

***Keywords*—Artificial Intelligence (AI) dependence; Science, Technology, Engineering, and Mathematics (STEM) education; time management; student engagement; Partial Least Squares Structural Equation Modeling (PLS-SEM); efficiency paradox**

I. INTRODUCTION

Generative Artificial Intelligence (GenAI) has emerged as a disruptive force in higher education, fundamentally altering how Science, Technology, Engineering, and Mathematics (STEM) students approach academic tasks. While these tools offer unprecedented opportunities for personalized tutoring, deeper conceptual understanding, and inclusive pedagogy, they simultaneously present complex challenges regarding academic integrity, ethical usage, and student satisfaction [1–3]. In the context of STEM education, where problem-solving and critical thinking are paramount, the integration of AI tools is no longer a matter of "if" but "how". Educational institutions are increasingly tasked with navigating this digital transformation, balancing the need for technological proficiency with the preservation of fundamental cognitive skills [4, 5].

However, a critical debate persists regarding the nature of student interaction with these technologies. While some scholars argue that AI serves as a powerful scaffold that augments human intelligence, others warn of a growing "AI Dependence" that may erode student agency and critical output [6, 7]. In this study, AI Dependence is operationally defined as a psychological state where students experience anxiety without access to AI tools and exhibit a tendency to offload critical thinking tasks to algorithms. This construct differs fundamentally from "perceived usefulness" or general "AI use", which denote the tool's utility and adoption frequency rather than an inability to function autonomously. Research indicates that heavy reliance on AI for answer-seeking, rather than brainstorming or verification, is linked to diminished analytical thinking and a potential "illusion of competence" where students overestimate their mastery of material [8, 9]. This tension creates a true "Efficiency Paradox": while students utilize AI to successfully expedite tasks and meet immediate deadlines, the pursuit of this short-term operational speed exacts a long-term psychological toll, rendering the student anxious and cognitively paralyzed when algorithmic assistance is unavailable. Despite the proliferation of studies on AI ethics and plagiarism, there is a scarcity of empirical research that models the specific psychological pathways such as perceived usefulness, motivation, self-efficacy, and digital literacy that drive this dependence [10].

Furthermore, the relationship between this dependence and actual Academic Productivity remains underexplored. In the context of this research, Output Productivity represents self-perceived academic efficiency, including the student's reported ability to meet deadlines and produce quality work within a reasonable timeframe. Does heavy reliance on AI actually lead to better output, or does it merely create an illusion of competence? The literature suggests that student engagement factors, particularly time management and perceived usefulness, play a pivotal role in mediating this relationship. While structured AI use is linked to better organization and task efficiency, stress-driven usage often correlates with procrastination and weaker performance [11, 12]. Understanding these mechanisms is crucial for developing policies that encourage AI as a productivity tool rather than a cognitive crutch.

Therefore, this study employs a descriptive-predictive correlational design using Partial Least Squares Structural Equation Modeling (PLS-SEM) to map the dual pathways of

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student engagement and AI dependence. Specifically, the research seeks to: (1) determine the level of student engagement across digital literacy, perceived usefulness, self-efficacy, motivation, and time management; (2) examine the influence of these engagement factors on AI Dependence; (3) analyze the direct and mediated effects of these factors on Student Output Productivity; and (4) utilize Importance-Performance Map Analysis (IPMA) to prioritize specific educational interventions for the "Efficiency Paradox" among tertiary STEM students.

II. Literature Review

A. Theoretical Framework

To explain the mechanism of AI dependence and productivity, this study integrates Uses and Gratifications Theory (UGT) and Social Cognitive Theory (SCT). UGT posits that students select media (AI tools) to satisfy specific needs, such as "information seeking" or "content generation". Research confirms that students adopt ChatGPT because it gratifies these utilitarian needs, but without critical literacy, this gratification can evolve into habitual dependence [13, 14]. Complementing this, SCT explains how personal factors (Self-Efficacy, Digital Literacy) interact with environmental factors to influence behavioral outcomes.

Legally, this investigation aligns with the UNESCO Guidance for Generative AI in Education and Research [15], which mandates the ethical integration of AI while guarding against cognitive atrophy. UNESCO emphasizes that while AI can support learning, institutions must implement frameworks that ensure "human oversight" and prevent the erosion of critical thinking skills caused by over-reliance [16, 17].

B. Influence of Digital Literacy (DL) on AI Dependence and Output Productivity

Digital Literacy in the AI era transcends basic computer skills; it involves "AI Literacy", the capacity to prompt, evaluate, and integrate AI outputs. While high digital literacy typically fosters autonomy, recent literature suggests a nuanced relationship. Students with lower digital literacy often view AI as a "black box" solution, leading to passive reliance and "shortcutting" behaviors [18, 19]. Conversely, AI-literate students tend to use GenAI as a collaborative partner, employing self-regulation to mitigate dependence risks while maximizing output quality [20, 21]. Hence, the following hypotheses are laid down:

H$_1$: Digital Literacy positively and significantly influences AI Dependence.

H$_2$: Digital Literacy positively and significantly influences Output Productivity.

C. Influence of Perceived Usefulness (PU) on AI Dependence and Output Productivity

Perceived Usefulness refers to the degree to which a student believes AI will enhance their performance. In STEM contexts, AI is often perceived as a critical scaffold for code debugging and complex problem-solving. Studies consistently show that high perceived usefulness is a strong predictor of both intentions to use and continued dependence [22–24]. However, this utility is also a primary driver of academic productivity, as students use the tool to automate routine tasks and generate ideas more efficiently [10, 25]. Thus, it is posited that:

H$_3$: Perceived Usefulness positively and significantly influences AI Dependence.

H$_4$: Perceived Usefulness positively and significantly influences Output Productivity.

D. Influence of Self-efficacy (SE) on AI Dependence and Output Productivity

Academic self-efficacy reflects a student's belief in their own capabilities. Theory suggests a negative relationship with dependence: highly confident students are less likely to rely on AI as a "crutch," using it instead as an optional "force multiplier." Conversely, students with low self-efficacy may exhibit "cognitive offloading," delegating core thinking tasks to the algorithm to manage academic anxiety [10, 26]. This "illusion of competence" can degrade authentic productivity over time if the student becomes unable to function without the tool [27]. Hence, the hypotheses below are suggested:

H$_5$: Self-Efficacy negatively and significantly influences AI Dependence.

H$_6$: Self-Efficacy positively and significantly influences Output Productivity.

E. Influence of Intrinsic Motivation (MO) on AI Dependence and Output Productivity

The literature categorizes student motivation as either intrinsic or extrinsic, with each type shaping AI interaction differently. Students driven by intrinsic motivation characterized by curiosity and the desire for mastery are hypothesized to exhibit lower AI dependence, utilizing these tools for exploration and feedback rather than simple answer-seeking [28, 29]. While extrinsic pressures often drive students toward AI shortcuts to bypass cognitive effort [30, 31], the measurement instrument in this study specifically captures intrinsic academic drive. Because intrinsically motivated learners prioritize deep cognitive engagement over mere task completion, this internal drive acts as a robust predictor of authentic productivity and a buffer against pathological dependence. Thus, the following hypotheses are proposed:

H$_7$: Intrinsic Motivation positively and significantly influences AI Dependence.

H$_8$: Intrinsic Motivation positively and significantly influences Output Productivity.

F. Influence of Time Management (TM) on AI Dependence and Output Productivity

Time Management represents the regulatory aspect of engagement. In high-pressure STEM environments, the efficiency offered by GenAI is a powerful lure. Students with strong time management skills may intentionally utilize AI to accelerate routine tasks, effectively trading cognitive load for speed [12, 32]. This "Efficiency Paradox" suggests that good time managers might actually display *higher* dependence on AI tools because they have integrated them into their workflow to maximize output [33, 34]. Thus, it is posited that:

H$_9$: Time Management positively and significantly influences AI Dependence.

H$_{10}$: Time Management positively and significantly influences Output Productivity.

G. Influence of AI Dependence (AD) on Output Productivity (OP)

AI Dependence is often framed negatively as a loss of agency. However, the relationship between dependence and productivity is complex. While unguided over-reliance can lead to "skill atrophy" and lower exam performance, functional reliance, where AI acts as a scaffold has been linked to significant gains in the speed and volume of academic output [35, 36]. Meta-analyses indicate that when integrated purposefully, AI tools can have a moderate to large positive effect on academic performance [37, 38]. This link underpins the final hypothesis:

H$_{11}$: AI Dependence positively and significantly influences Output Productivity.

In summary, the research hypotheses developed in this study are visually represented in the proposed conceptual framework, as illustrated in Fig. 1.

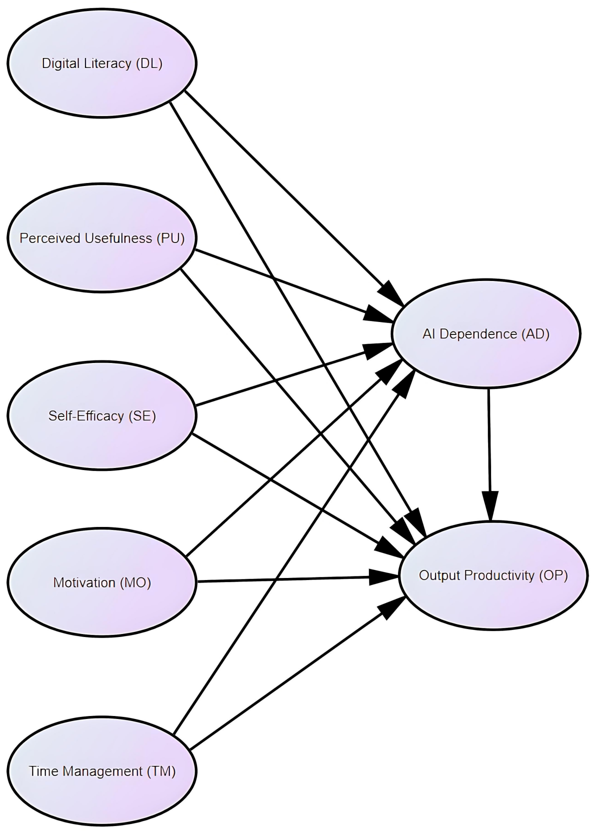

Fig. 1. Proposed conceptual framework.

III. Materials and Methods

A. Methodology

1) Research design

This study employed a descriptive-predictive correlational research design to model the structural relationships between student engagement, AI dependence, and output productivity. Unlike experimental designs that manipulate variables, this approach is appropriate for identifying the causal-predictive linkages in naturalistic educational settings without intervention [39, 40]. The study utilized Partial Least Squares Structural Equation Modeling (PLS-SEM) as the primary statistical tool. PLS-SEM was selected over Covariance-Based SEM (CB-SEM) because the research objective is prediction-oriented, specifically to identify the key drivers of productivity rather than theory confirmation [41]. Furthermore, PLS-SEM is robust for handling complex models with non-normal data often found in behavioral surveys and offers superior out-of-sample predictive power [42, 43]. This methodological choice aligns with recent scholarship demonstrating that PLS-SEM is particularly effective for modeling the direct structural links between technology acceptance factors and student performance outcomes [44].

2) Participants and sampling

The study involved a total of 915 undergraduate students enrolled in STEM-aligned programs at a state university in the southern Philippines. The sampling utilized a purposive-convenience strategy. The purposive criterion ensured all participants were enrolled in technical or technology-focused curricula (Industrial Technology, Engineering, Computing, or Science Education), while convenience sampling was employed to maximize participation rates within available course sections during the data collection period.

As detailed in Table 1, the sample was predominantly composed of Bachelor of Industrial Technology (BIndTech) students (62.3%), specifically those majoring in Mechanical/Automotive and Electrical/Electronics technologies. This aligns with the study's focus on technical skill acquisition. Regarding academic progression, the sample was heavily weighted towards Second Year students (69.8%), followed by Third Year (18.7%). The heavy skew toward Industrial Technology and second-year cohorts serves as a highly valid proxy for the target population, as these demographics represent the critical developmental phase where students transition from foundational theory to applied, software-dependent technological execution. Furthermore, a post-hoc power analysis utilizing G*Power confirmed that the sample of 915 provides >0.99 statistical power to detect small effect sizes (f^2 = 0.02) in a structural model with six predictors, ensuring robust generalizability within the specified context.

Table 1. Demographic profile of respondents (N = 915)

<table>
<tr><th>Profile Category</th><th colspan="2">Sub-Category</th><th>Frequency</th><th>Percentage (%)</th></tr>
<tr><td rowspan="9">Degree Program</td><td rowspan="3">Bachelor of Industrial Technology (BIndTech)</td><td>Mechanical/ Automotive Tech</td><td>381</td><td>41.64</td></tr>
<tr><td>Electrical / Electronics Tech</td><td>171</td><td>18.69</td></tr>
<tr><td>Computer Technology</td><td>18</td><td>1.97</td></tr>
<tr><td rowspan="3">Computing & Engineering</td><td>BS Information Technology</td><td>63</td><td>6.89</td></tr>
<tr><td>BS Computer Engineering</td><td>57</td><td>6.23</td></tr>
<tr><td>BS Computer Science</td><td>33</td><td>3.61</td></tr>
<tr><td>Teacher Education</td><td>Bachelor of Secondary Education (STEM)</td><td>192</td><td>20.98</td></tr>
<tr><td rowspan="4">Year Level</td><td colspan="2">First Year</td><td>72</td><td>7.87</td></tr>
<tr><td colspan="2">Second Year</td><td>639</td><td>69.84</td></tr>
<tr><td colspan="2">Third Year</td><td>171</td><td>18.69</td></tr>
<tr><td colspan="2">Fourth Year</td><td>33</td><td>3.61</td></tr>
<tr><td>Total</td><td colspan="2"></td><td>915</td><td>100.00</td></tr>
</table>

3) Research instrument

Data were collected using a structured, web-based questionnaire divided into seven sections representing the latent constructs: Digital Literacy (DL), Perceived Usefulness (PU), Self-Efficacy (SE), Intrinsic Motivation (MO), Time Management (TM), AI Dependence (AD), and self-perceived Output Productivity (OP) (see Table A1). The items were adapted from established scales in educational technology literature to ensure content validity [45, 46]. All items were measured using a 5-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). Prior to full deployment, the instrument underwent a rigorous validation process. First, content validity was assessed by three educational technology experts to ensure item clarity and relevance to the STEM context. Second, a pilot test was conducted with 50 non-participant students. Cronbach's Alpha analysis confirmed internal consistency, with all constructs exceeding the 0.70 threshold.

This study adhered to the ethical protocols of the Declaration of Helsinki. Ethical approval was granted by the Research Ethics Committee of the host university (Protocol/Ref: NEMSU-RDO-2025-08). Informed consent was obtained digitally from all participants, ensuring anonymity and the right to withdraw.

B. *Data Analysis*

The data analysis proceeded in two phases using SmartPLS 4.0.

(1) Partial Least Square Structural Equation Modeling: The measurement model was assessed for convergent and discriminant validity, followed by the structural model assessment to test the 11 hypothesized paths and determine the explanatory power (R^2) of the framework.

(2) Importance-Performance Map Analysis (IPMA): To extend the findings beyond standard coefficient analysis, IPMA was conducted for the target construct "Output Productivity." This advanced post-hoc analysis contrasts the "Importance" (Total Effect) of a precursor against its current "Performance" (Index Value), allowing for the identification of high-priority areas for managerial and pedagogical intervention [47, 48].

IV. Result

A. *Measurement Model Assessment*

The reliability and validity of the reflective constructs were evaluated using SmartPLS 4.0. As presented in Table 2, the measurement model demonstrated exceptional internal consistency. Cronbach's Alpha (α) values for all constructs ranged from 0.960 to 0.984, well above the 0.70 threshold. Similarly, Composite Reliability values exceeded 0.96, indicating high reliability. Convergent validity was established with Average Variance Extracted (AVE) values ranging from 0.734 (Digital Literacy) to 0.878 (AI Dependence), surpassing the 0.50 benchmark. These metrics confirm that the survey instrument was robust and psychometrically sound for the target STEM population.

Given the reliance on cross-sectional self-reported data, the potential for Common Method Bias (CMB) was assessed. First, Harman's Single Factor test was conducted via an unrotated exploratory factor analysis. The single largest factor accounted for 56.12% of the total variance. Because this value slightly exceeds the conservative 50% threshold, a secondary assessment was conducted to verify discriminant validity at the construct level, as Harman's test is often overly sensitive in complex behavioral models. Following Pavlou *et al.* [49], an inspection of the inter-construct correlation matrix (Table 3) revealed that the highest correlation between any two latent variables was 0.852 (between Digital Literacy and Perceived Usefulness). Because no correlation exceeded the critical 0.90 threshold, evidence suggests that the constructs are empirically distinct and that CMB does not severely inflate or confound the structural relationships in this model.

Table 2. Construct reliability and validity

Construct	Cronbach's α	Composite Reliability	AVE
AI Dependence (AD)	0.984	0.985	0.878
Digital Literacy (DL)	0.960	0.962	0.734
Motivation (MO)	0.966	0.967	0.764
Output Productivity (OP)	0.975	0.975	0.817
Perceived Usefulness (PU)	0.975	0.975	0.818
Self-Efficacy (SE)	0.966	0.966	0.766
Time Management (TM)	0.970	0.970	0.787

B. *Discriminate Validity*

Discriminant validity was assessed using the Fornell-Larcker criterion. As shown in Table 3, the square root of the AVE for each construct (bolded values on the diagonal) was consistently higher than its correlation with any other construct. This confirms that the seven constructs are empirically distinct, ensuring that "Dependence" is measured separately from "Usefulness" or "Engagement."

Table 3. Discriminant validity (Fornell-Larcker Criterion)

	AD	DL	MO	OP	PU	SE	TM
AD	**0.937**						
DL	0.574	**0.857**					
MO	0.405	0.695	**0.874**				
OP	0.542	0.635	0.753	**0.904**			
PU	0.592	0.852	0.633	0.623	**0.904**		
SE	0.524	0.698	0.826	0.667	0.662	**0.875**	
TM	0.539	0.606	0.791	0.840	0.600	0.756	**0.887**

C. *Structural Model Assessment*

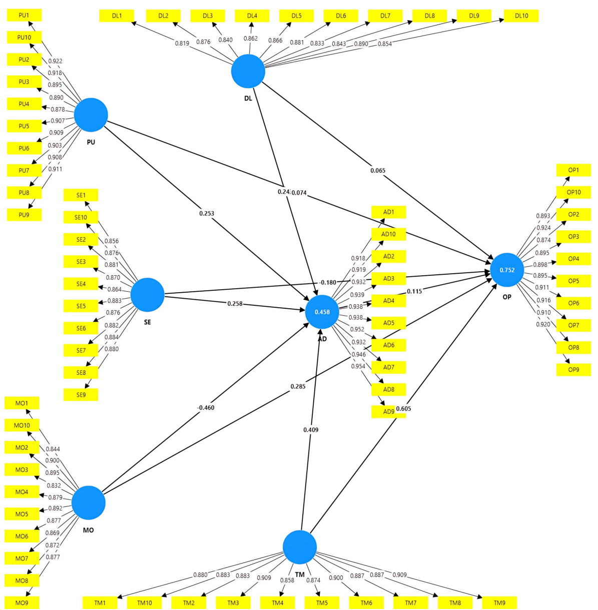

Fig. 2. The structural model showing path coefficients and R^2 values.

Prior to assessing the structural paths, the inner Variance Inflation Factor (VIF) values were examined to check for collinearity issues among the predictor constructs. The inner VIF values ranged from 1.845 to 5.449. While the ideal threshold is below 3.0, the maximum recorded value (5.449) remains well below the strict upper limit of 10.0 and closely borders the accepted 5.0 benchmark for PLS-SEM [50]. Given the robust sample size ($N = 915$), collinearity was not considered a severe threat to the validity of the regression results.

The structural model was evaluated to test the hypothesized relationships between engagement factors, AI dependence, and productivity. The final model, including path coefficients and explanatory power, is visualized in Fig. 2.

D. Predictive Power (R^2) and Predictive Relevance (Q^2)

The model explained a substantial amount of variance in the endogenous constructs. Specifically, the engagement factors accounted for 45.8% ($R^2 = 0.458$) of the variance in AI Dependence, and 75.2% ($R^2 = 0.752$) of the variance in Student Output Productivity, indicating a very high level of in-sample predictive accuracy. Furthermore, the PLSpredict procedure was utilized to assess out-of-sample predictive relevance (Q^2). The $Q^2_{predict}$ values for AI Dependence (0.448) and Output Productivity (0.738) were considerably greater than zero, confirming the model's strong predictive relevance for new data.

E. Hypothesis Testing and Effect Size (f^2)

The bootstrapping procedure (5000 subsamples) was used to assess the significance of the path coefficients, while the f_2 metric was utilized to determine the effect size of each predictor. As detailed in Table 4, the analysis supported 8 out of the 11 proposed hypotheses.

Table 4. Structural model path coefficients and effect sizes

Hypothesis	Path Relationship	β (Beta)	T-Statistics	P-Values	f^2 Effect Size	Decision
H1	DL-AD	0.243	3.395	**0.001**	0.020	Supported
H2	DL-OP	0.065	1.530	0.126	0.003	Rejected
H3	PU-AD	0.253	3.269	**0.001**	0.025	Supported
H4	PU-OP	0.074	1.486	0.137	0.005	Rejected
H5	SE-AD	0.258	4.877	**0.000**	0.032	Rejected
H6	SE-OP	**–0.180**	3.324	**0.001**	0.033	Supported
H7	MO-AD	**–0.460**	6.824	**0.000**	0.092	Supported
H8	MO-OP	0.285	7.713	**0.000**	0.071	Supported
H9	TM-AD	0.409	6.560	**0.000**	0.103	Supported
H10	TM-OP	**0.605**	15.845	**0.000**	0.445	Supported
H11	AD-OP	0.115	4.465	**0.000**	0.029	Supported

The results revealed complex pathways. Time Management emerged as a critical dual-driver, positively influencing AI Dependence ($\beta = 0.409$, $p < 0.001$, $f^2 = 0.103$) and exerting a large effect on Output Productivity ($\beta = 0.605$, $p < 0.001$, $f^2 = 0.445$). This confirms the "Efficiency Paradox," where better time managers rely more on AI to boost output. Conversely, Intrinsic Motivation showed a significant negative influence on AI Dependence ($\beta = -0.460$, $p < 0.001$, $f^2 = 0.092$), suggesting that highly motivated students are less likely to become dependent. However, H5 was rejected; while the relationship between Self-Efficacy and AI Dependence was significant, it was positive rather than the hypothesized negative direction ($\beta = 0.258$, $p < 0.001$, $f^2 = 0.032$). Interestingly, Self-Efficacy also had a negative direct effect on Productivity ($\beta = -0.180$, $p = 0.001$, $f^2 = 0.033$), indicating a potential overconfidence effect.

F. Importance-Performance Map Analysis (IPMA)

To prioritize managerial interventions, an IPMA was conducted for the target construct Output Productivity. As shown in Table 5 and Fig. 3, Time Management exhibited the highest importance (Total Effect = 0.651) but relatively lower performance (79.32) compared to Digital Literacy (84.49). Notably, AI Dependence showed low importance (0.115) despite a performance index of 72.97.

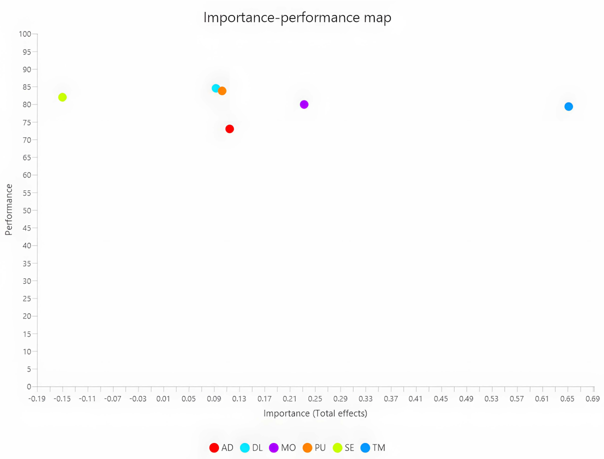

Fig. 3. Importance-performance map result.

Table 5. IPMA results for output productivity

Construct	Importance (Total Effect)	Performance (Index)
Time Management (TM)	**0.651**	79.327
Motivation (MO)	0.232	79.913
AI Dependence (AD)	0.115	72.977
Perceived Usefulness (PU)	0.103	83.756
Digital Literacy (DL)	0.093	84.497
Self-Efficacy (SE)	–0.150	81.962

V. Discussion

This study empirically modeled the "Efficiency Paradox" in STEM education, examining how student engagement factors drive AI dependence and, subsequently, academic productivity. The structural model explained a substantial

75.2% of the variance in productivity, offering a robust explanation for how GenAI is reshaping student workflows.

A. The Efficiency Paradox: Time Management as the Double-Edged Sword

The most pivotal finding is the dual role of Time Management (TM). It emerged as the strongest positive predictor of both AI Dependence (β = 0.409) and Output Productivity (β = 0.605). Furthermore, the IPMA identified TM as the single most critical driver of productivity (Importance = 0.651). This confirms the hypothesis that for STEM students facing rigorous coursework, AI is primarily operationalized as an efficiency tool. This creates a calculated trade-off: students willingly accept the psychological cost of anxiety and reliance (as measured by the AD construct) in exchange for the immediate operational speed required to manage heavy workloads [12, 32]. Therefore, AI dependence in this context is not merely a lack of competence, but a strategic, albeit psychologically taxing, adaptation to high-stakes academic environments [33].

B. Motivation as a Buffer Against Dependence

A striking finding is the strong negative relationship between Motivation (MO) and AI Dependence (AD) (β = −0.460). This implies that students who are intrinsically motivated, those who find value and enjoyment in the learning process itself, are significantly *less* likely to rely on AI. Intrinsically motivated learners likely use AI for feedback or exploration (scaffolding) rather than outsourcing the cognitive labor (substitution) [28]. Conversely, students with lower motivation may turn to AI as a shortcut to bypass effort, increasing dependence. This supports the argument by Fan *et al.* [30] that "metacognitive laziness" is a risk primarily for those lacking intrinsic drive.

C. The Illusion of Competence: Self-Efficacy and Digital Literacy

Contrary to expectations, Self-Efficacy (SE) had a negative direct effect on Productivity (β = −0.180). This counter-intuitive finding suggests an "Overconfidence Effect" or Dunning-Kruger manifestation. Beyond the context of AI usage, this phenomenon frequently occurs in rigorous STEM disciplines. Rather than mere overconfidence, this suggests a phenomenon of active resistance. Highly self-efficacious students may consciously choose to bypass AI assistance, prioritizing traditional cognitive depth over algorithmic acceleration. Consequently, by relying entirely on manual execution, these confident students sacrifice operational speed and appear statistically less "productive" on efficiency metrics compared to their highly dependent, AI-assisted peers [27]. Additionally, while Digital Literacy (DL) and Perceived Usefulness (PU) were high among respondents (IPMA Performance >83), they had a negligible direct impact on productivity (Importance <0.10). This indicates a "Saturation Effect," where basic digital skills are now a hygiene factor. Recent literature explains this saturation through the lens of system familiarity; as students become accustomed to intelligent systems, convenience outweighs novelty [39]. Consequently, recognizing an AI tool as useful (PU) no longer guarantees output gains. Future productivity relies entirely on the sophistication of active learning strategies and regulatory behaviors such as time management employed by the user [19, 39].

D. Implications and Recommendations

1) Theoretical implications

This study contributes to the literature by validating the integration of Uses and Gratifications Theory and Social Cognitive Theory within the GenAI context. By identifying a "Strategic Dependence" mechanism, the study challenges the deficit model often associated with UGT (where dependence is seen as passive gratification). Instead, it demonstrates that high-performing STEM students actively leverage AI to satisfy "process gratification" needs (efficiency), effectively creating a new theoretical category of "Regulatory Dependence".

2) Practical implications (based on IPMA)

(1) Rebalance Training Toward Self-Regulation: Since Digital Literacy and Perceived Usefulness already show high performance (saturation), universities should rebalance their resource allocation. Rather than focusing exclusively on basic software operation, institutions should integrate targeted AI literacy (focusing on verification and ethical use) with advanced training in Time Management and Self-Regulated Learning. To operationalize this, curriculum designers should implement scaffolded AI assignments where time constraints are intentionally manipulated to force self-regulation. AI adoption in immersive educational ecosystems, instructors should adopt process-oriented assessments that grade the student's workflow and prompt-engineering strategy rather than merely evaluating the final generated output. This pedagogical shift prevents strategic AI use from degrading into pathological dependence.

(2) Redesign for Intrinsic Engagement: To combat harmful dependence, educators must design assessments that spark curiosity (Motivation). When students care about the *process*, the negative path to dependence strengthens.

(3) Calibration of Confidence: Instructors should implement exercises that help students calibrate their Self-Efficacy, ensuring that confidence does not lead to complacency or the rejection of necessary productivity tools.

VI. Conclusion

A. Conclusion

This study empirically modeled the "Efficiency Paradox" in STEM education, examining how specific student engagement factors Digital Literacy, Perceived Usefulness, Self-Efficacy, Motivation, and Time Management drive AI dependence and perceived academic productivity.

The findings lead to three pivotal conclusions. First, Time Management is the primary driver of both Dependence and Productivity. The robust positive influence of Time Management on both constructs confirms that students utilize GenAI primarily as a "speed multiplier" to cope with rigorous academic demands. Second, Intrinsic Motivation acts as a cognitive shield. Students who find genuine enjoyment in learning are significantly less likely to become dependent on algorithms, using them instead as supplementary scaffolds. Third, Self-Efficacy presents a double-edged sword. The negative impact of high self-confidence on productivity suggests a potential "overconfidence effect", where students may underestimate the necessity of leveraging tools effectively to meet output standards.

Ultimately, this study concludes that perceived academic productivity is not defined by Digital Literacy alone, but by Regulatory Skills. While students possess high levels of digital proficiency, it is their ability to manage time and internal motivation that determines whether AI becomes a productive tool or a source of passive dependence.

B. Limitations and Future Research

While this study benefits from a robust sample ($N = 915$), interpretations must consider the geographic limitation of collecting data from a single state university in the southern Philippines. Consequently, generalizability to other cultural or institutional contexts may be limited. Future research should employ stratified random sampling across multiple universities to validate these findings globally. Additionally, while PLS-SEM provides strong predictive capabilities, the cross-sectional nature of the data precludes strict causal inference; longitudinal designs are recommended to track if "Strategic Dependence" evolves into "Skill Atrophy" over time. Finally, the study relies on self-reported measures. Because highly dependent students may suffer from an illusion of competence, their self-rated productivity may outpace objective observer evaluations. Subsequent studies should utilize objective performance metrics, such as verifiable LMS log data or actual GPA.

Furthermore, the current framework predominantly captures individual psychological resources. Future holistic models must integrate institutional factors such as university infrastructure, system quality, and administrative support as critical antecedents that shape student satisfaction and AI adoption in immersive educational ecosystems [40]. Additionally, the Digital Literacy construct measured generalized comfort with digital platforms. In the GenAI era, future research should employ granular instruments that specifically measure advanced AI literacy, including algorithmic understanding and prompt engineering. Crucially, the construct of Output Productivity utilized in this study primarily measures execution speed and workload management rather than innovative generation. Future empirical work must distinguish between operational efficiency and technological creativity to determine whether AI dependence inhibits or enhances novel problem-solving in engineering disciplines.

APPENDIX

Table A1. Constructs of the instruments with the items assigned and their corresponding sources

Construct	Items and Codes	No. of Items	References (Theoretical & Empirical Anchors)
Digital Literacy (DL)	**DL1.** I can effectively search for academic information using digital tools and online platforms. **DL2.** I can evaluate the credibility of information generated by AI tools. **DL3.** I am confident in using AI tools for academic purposes such as research and writing. **DL4.** I understand the ethical implications of using AI in academic work. **DL5.** I can integrate AI-generated information with my own academic understanding. **DL6.** I can troubleshoot basic technical issues when using AI-based applications. **DL7.** I am aware of the limitations of AI-generated content. **DL8.** I can appropriately cite or acknowledge AI-assisted outputs when required. **DL9.** I can adapt to new AI tools introduced for academic use. **DL10.** I use AI tools responsibly to support my learning activities.	10	[18–20, 51]
Perceived Usefulness (PU)	**PU1.** AI tools improve the quality of my academic work. **PU2.** AI tools help me complete academic tasks more efficiently. **PU3.** AI enhances my understanding of complex academic concepts. **PU4.** AI tools are useful for generating ideas for assignments and projects. **PU5.** AI supports my learning by providing immediate feedback or explanations. **PU6.** AI tools increase my academic productivity. **PU7.** Using AI helps me manage academic workload more effectively. **PU8.** AI tools are valuable resources for academic problem-solving. **PU9.** AI improves my performance in academic tasks. **PU10.** Overall, AI tools are beneficial to my academic success.	10	[22, 23, 25, 52]
Self-Efficacy (SE)	**SE1.** I am confident in completing academic tasks even without AI assistance. **SE2.** I believe I can produce quality academic work on my own. **SE3.** I can successfully complete challenging academic tasks. **SE4.** I feel capable of learning difficult topics independently. **SE5.** I am confident in managing academic requirements effectively. **SE6.** I believe I can solve academic problems without relying heavily on AI. **SE7.** I can meet academic deadlines through my own effort. **SE8.** I am confident in applying my knowledge to academic tasks. **SE9.** I believe my academic performance depends mainly on my abilities. **SE10.** I can achieve academic goals through consistent effort.	10	[10, 26, 27, 53]
Motivation (MO)	**MO1.** I am motivated to complete academic tasks even when they are difficult. **MO2.** I enjoy learning new concepts related to my field of study. **MO3.** I feel enthusiastic about completing academic requirements. **MO4.** I am motivated to improve my academic performance. **MO5.** I persist in completing academic tasks despite challenges. **MO6.** I set personal goals for my academic success. **MO7.** I feel a sense of accomplishment when completing academic tasks. **MO8.** I am motivated to learn even without external rewards. **MO9.** I actively engage in academic activities.	10	[28–30, 54]

	MO10. I am committed to achieving my academic goals.		
Time Management (TM)	**TM1.** I plan my academic tasks ahead of time. **TM2.** I prioritize academic tasks effectively. **TM3.** I allocate sufficient time for studying and assignments. **TM4.** I avoid procrastination in completing academic work. **TM5.** I manage deadlines effectively. **TM6.** I balance academic tasks with other responsibilities. **TM7.** I complete academic tasks within the allotted time. **TM8.** I follow a structured schedule for academic activities. **TM9.** I use time efficiently when working on academic tasks. **TM10.** I can manage multiple academic tasks simultaneously.	10	[12, 32, 33]
AI Dependence (AD)	**AD1.** I feel anxious when I cannot access AI tools for my assignments. **AD2.** I rely on AI to start almost every academic writing task. **AD3.** I often use AI to complete tasks without fully understanding the content myself. **AD4.** I find it difficult to generate ideas without the help of AI. **AD5.** I spend less time critical thinking because AI does the work for me. **AD6.** I feel that I cannot compete academically without using AI tools. **AD7.** I prefer using AI to solve problems rather than trying to solve them myself first. **AD8.** I tend to accept AI-generated answers without verifying them thoroughly. **AD9.** I feel stranded or stuck if AI tools are offline or unavailable. **AD10.** My confidence in my work drops significantly if I haven't used AI to check it.	10	[10, 13, 14]
Output Productivity (OP)	**OP1.** I complete academic tasks efficiently. **OP2.** I consistently meet academic deadlines. **OP3.** I produce high-quality academic outputs. **OP4.** I can complete academic tasks within a reasonable time. **OP5.** My academic work meets course expectations. **OP6.** I am satisfied with the quality of my academic outputs. **OP7.** I can manage academic workload effectively. **OP8.** I perform well in academic assessments. **OP9.** I am productive during academic activities. **OP10.** I consistently achieve expected academic outcomes.	10	[11, 35, 37, 38]

Conflict of Interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Author Contributions

KG: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Visualization, Writing—original draft, Writing—review & editing, Supervision. JB: Conceptualization, Validation, Writing—review & editing, Methodology, Validation, Writing—review & editing. All authors had approved the final version.

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