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DO INSTITUTIONAL AI POLICIES RELATE TO STUDENT AI DEPENDENCY? EVIDENCE FROM INFORMATION TECHNOLOGY STUDENTS

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ABSTRACT

This quantitative descriptive–correlational study examined whether awareness of and compliance with an institutional AI Use Policy are associated with lower dependency on AI tools among Information Technology students. As generative AI tools (e.g., ChatGPT) become common in higher education, overreliance may weaken independent learning skills, yet empirical evidence linking institutional policy to AI dependency remains limited (Ghimire & Edwards, 2024). Data were collected from 168 undergraduate IT students in the Philippines. The survey measured AI use frequency and purposes, AI dependency using the AI Dependency Index (AIDI; 15 items), study habits, academic performance (GWA), and policy awareness and compliance. Descriptive statistics, t-tests, and multiple regression were applied. Most students reported frequent AI use (73.2% daily or several times weekly), primarily for understanding concepts (83.3%) and coding/debugging (62.5%), with 36.9% using AI for research/summarizing. Overall AI dependency was moderate ($M = 2.78$). Students aware of the policy reported lower AI dependency than those unaware, $t(166) = -2.25$, $p = .026$. In regression, policy compliance significantly predicted lower AI dependency ($\beta = -0.290$, $p < .001$), while study habits ($p = .246$) and academic performance ($p = .168$) were not significant predictors. Findings suggest that stronger policy communication and reinforcement may help reduce student AI dependency.

KEYWORDS: *AI Dependency; Institutional Policy; ChatGPT; Self-Regulated Learning; Information Technology Education; AIDI*

1. INTRODUCTION

Generative AI systems such as ChatGPT are increasingly embedded in academic work, particularly in computing and Information Technology (IT) education. Students commonly use these tools for explanations, feedback, and coding assistance, enabling faster task completion and conceptual support (Bringula, 2024). In the Philippine context, the use of ChatGPT for academic research has been documented across different educational levels, indicating its rapid integration into learning practices (Cabuquin et al., 2024).

Despite these benefits, emerging research suggests that heavy reliance on generative AI may be associated with weaker self-regulated learning behaviors and problematic usage patterns (Morales-Garcia et al., 2024; Zhang et al., 2024). Self-Regulated Learning (SRL) Theory emphasizes learners' active engagement in planning, monitoring, and self-evaluating their learning processes (Zimmerman, 2000). When students frequently substitute effortful thinking with AI-generated outputs, opportunities for metacognitive engagement and independent problem-solving may be reduced.

From an institutional perspective, Feenberg's Critical Theory of Technology highlights that technologies are shaped by social and organizational norms rather than being neutral tools (Feenberg, 1999). Accordingly, institutional policies may play a crucial role in shaping whether generative AI supports learner autonomy or fosters dependency. While international guidance on responsible generative AI use in education is expanding (UNESCO, 2023; Jin et al., 2025), policy coverage and enforcement remain uneven, and empirical evidence linking policy awareness and compliance to AI dependency is still limited (Ghimire & Edwards, 2024).

In the Philippines, initial efforts have been made to operationalize and measure AI dependency through locally developed and validated instruments, such as the AI Dependency Index (AIDI)

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(Capinding, 2024). However, evidence examining the relationship between institutional AI policies and AI dependency among IT students remains scarce. As generative AI increasingly becomes a routine help-seeking tool for computing learners (Hou et al., 2025), this study examines AI usage patterns, AI dependency as measured by the AIDI, study habits, academic performance, and institutional AI policy awareness and compliance among IT students. Anchored in SRL Theory and Feenberg's Critical Theory of Technology, AI dependency (AIDI score) is treated as the outcome variable, with institutional AI policy factors and academic-related variables examined as predictors, while AI usage patterns provide descriptive context for understanding students' engagement with generative AI.

2. OBJECTIVES

This study aims to examine generative AI use and dependency among Information Technology students. Specifically, it seeks to:

1. Determine the frequency and primary academic purposes of using free AI tools among IT students.
2. Assess the level of AI dependency among IT students as measured by the AI Dependency Index (AIDI).
3. Examine the relationship between AI dependency and students' study habits, academic performance, and institutional AI policy awareness and compliance.
4. Identify implications of the findings for developing strategies that promote responsible and pedagogically sound integration of generative AI in IT education.

3. METHODOLOGY

3.1 Research Design

A quantitative descriptive-correlational design was used to examine relationships among AI usage patterns, AI dependency, academic-related factors, and institutional AI policy awareness and compliance.

3.2 Instruments

Data were collected via a structured questionnaire with five sections: (1) demographics and self-reported academic performance (GWA), (2) AI usage patterns (frequency and purposes), (3) AI Dependency Index (AIDI; 15 items), (4) study habits (4 items measuring independent study behavior and perceived efficiency when using AI tools), and (5) AI policy awareness and compliance (4 items). The AIDI item pool was adapted from published AI-dependency measurement approaches, particularly the Scale of Dependency toward Artificial Intelligence (DIA) (Morales-Garcia et al., 2024). Items were contextualized to common IT academic tasks (e.g., code explanation, debugging, writing support). Content validity was established through expert review by IT faculty members. Reliability testing showed high internal consistency for the AIDI (Cronbach's $\alpha = .86$) and acceptable to high reliability for the other scales ($\alpha > .80$).

3.3 Data Collection and Ethics

Data were collected online using Google Forms. Ethical safeguards included informed consent, voluntary participation, anonymity, and instructions asking respondents to answer without using AI tools. Submissions were screened for completeness prior to analysis. Data were analyzed using Microsoft Excel (Data Analysis ToolPak).

4. SAMPLING DESIGN

A total enumeration approach targeted all 206 undergraduate IT students enrolled across year levels at the University of La Salette, Santiago City, Philippines. A total of 168 students provided complete responses (81.6% response rate), representing all BSIT year levels.

5. STATISTICAL DESIGN

Descriptive statistics were used to summarize patterns of AI tool use and AI Dependency Index (AIDI) scores. Group differences in AI dependency by institutional AI policy awareness were examined using independent-samples *t*-tests. To identify factors associated with AI dependency, a multiple linear regression model was estimated with policy compliance, study habits, and general weighted average (GWA) entered as predictors. All tests were two-tailed, and statistical significance was evaluated at $\alpha = .05$.

6. GEOGRAPHICAL AREA

The study was conducted at University of La Salette, Inc., located in Santiago City, Isabela, Philippines. The institution serves learners from the city and nearby municipalities in the Cagayan Valley, providing a relevant setting for examining student use of free AI tools that are typically accessed through mobile devices and internet-connected computers. Data were gathered from enrolled undergraduate Information Technology students during the conduct of the survey.

7. RESULTS AND DISCUSSION

7.1 Reliability and Respondent Profile

A total of 168 undergraduate IT students participated in the study. All measurement instruments demonstrated acceptable to high reliability (Cronbach's $\alpha > .80$), with the AI Dependency Index (AIDI) showing strong internal consistency ($\alpha = .86$) (Table 1). Respondents represented all academic year levels, with comparable academic performance across cohorts (Tables 2 and 3).

Academic performance across year levels remained generally high and stable, with an overall mean GWA of 86.93. Minimal variation across year levels suggests consistent academic standards and learning outcomes throughout the program.

7.2 AI Usage Patterns and the Spectrum of Engagement

A combined 73.2% of students used AI daily (26.2%) or several times a week (47.0%) (Table 4). The most common purposes were understanding lessons or concepts (83.3%), coding/debugging (62.5%), and research/summarizing (36.9%); fewer used AI for writing (33.3%) and exam/quiz preparation

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(24.4%) (Table 5). These results are consistent with prior findings that computing students use generative AI for routine academic support (Hou et al., 2025; Cabuquin et al., 2024).

7.3 AI Dependency Levels and Item Patterns (AIDI)

Overall, AI dependency was moderate (M = 2.78) (Table 7): 44.0% low, 45.2% moderate, and 10.7% high. The highest item means reflected efficiency and routine use – "AI tools help me finish tasks faster" (M = 3.41) and "AI tools have become an essential part of my academic routine" (M = 3.06) (Table 6). Items on checking outputs and confidence without AI (Items 18–19; reverse-scored in the total) were also relatively high, suggesting many students treat AI as support rather than a full substitute for independent work (Bringula, 2024; Manorat et al., 2025).

7.4 Dependency, Self-Regulation, and Performance

Descriptively, Study Habits indicators were satisfactory (Table 8), but Study Habits did not significantly predict AI dependency in the regression model (p = .246), and GWA was also not a significant predictor (p = .168) (Table 11). Although self-regulated learning remains theoretically important for interpreting help-seeking and independent learning behaviors (Zimmerman, 2000), the findings suggest that policy-related factors were more directly associated with AI dependency in this sample. This pattern is consistent with evidence that contextual and governance factors can shape AI-related behavior beyond individual academic characteristics (Zhang et al., 2024).

7.5 The Role of Institutional AI Policy

Most respondents were aware of the institutional AI Use Policy (87.5%), and 84.5% reported high/moderate compliance; the remaining 15.5% reported low compliance or were unaware (Table 9). Policy-aware students had significantly lower AI dependency than those unaware (Table 10). The regression model was significant, $F(3, 164) = 5.54$, $p = .001$ ($R^2 = .092$), and policy compliance was the strongest predictor of lower AI dependency ($B = -0.137$, $\beta = -0.290$, $p < .001$) (Table 11). Consistent with Feenberg's Critical Theory of Technology, institutional policy can shape how generative AI is practiced in academic work (Feenberg, 1999) and aligns with guidance for responsible AI use in education (UNESCO, 2023; Jin et al., 2025).

8. SUGGESTIONS

Given that compliance predicted lower dependency, make the AI policy more practical by providing clear task-specific rules (e.g., for coding, writing, and research). Instructors can add brief reflection activities and adjust assessments so students apply the policy in authentic course tasks, not only understand it. Along with the policy, provide basic AI literacy lessons so students learn to evaluate AI outputs, avoid errors, and use AI responsibly (UNESCO, 2023; Jin et al., 2025).

9. CONCLUSION

AI dependency among IT students was moderate in this sample (M = 2.78). Students who were aware of the institutional AI policy—and especially those reporting higher compliance—showed lower AI dependency. In the regression model, policy compliance was the only statistically significant predictor of AI dependency, while study habits and academic performance were not significant predictors. These findings suggest that clear communication and consistent reinforcement of AI use policies may help guide students toward more controlled and responsible AI use.

10. AREA FOR FURTHER RESEARCH

This study used a cross-sectional design and self-reported data, so it cannot prove cause-and-effect and may include response bias. The study was also limited to one institution, so results may not represent other schools. Future studies may use longitudinal or mixed-method approaches and include multiple institutions to better understand how policy implementation relates to AI use behavior over time.

11. TABLES AND REFERENCES

11.1 Tables

Table 1. Reliability Statistics of the Study Scales

Scale	Number of Items	Cronbach's α
AI Dependency Index (AIDI)	15	.86
Academic-Related Factors (Study Habits)	4	.84
AI Policy Awareness and Compliance	4	.91

Table 2. Demographic Profile of Respondents

Variable	Category	Frequency (f)	Percentage (%)
Gender	Male	134	79.8
	Female	31	18.5
	Prefer not to say	3	1.7
Year Level	1st Year	53	31.5
	2nd Year	58	34.5
	3rd Year	30	17.9
	4th Year	27	16.1

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Table 3. Mean and Standard Deviation of GWA by Year Level

Year Level	Mean GWA	SD
1st Year	86.62	3.32
2nd Year	87.14	3.51
3rd Year	87.55	3.48
4th Year	86.41	3.25
Overall	86.93	3.40

Table 4. Frequency of AI Tool Usage

Usage Frequency	Frequency (f)	Percentage (%)
Daily	44	26.2
Several times a week	79	47.0
Once a week	21	12.5
Rarely	22	13.1
Never	2	1.2

Table 5. Academic Purposes of AI Use

Note. Multiple responses were allowed.

Purpose	Frequency (f)	Percentage (%)
Understanding lessons or concepts	140	83.3
Coding or debugging assistance	105	62.5
Research or summarizing articles	62	36.9
Writing assignments or reports	56	33.3
Exam or quiz preparation	41	24.4

Table 6. AI Dependency Index (AIDI) Item Means (n = 168)

Note. Items 18–19 were reverse-scored when computing the AIDI total/mean score; item means shown here are in the original (non-reversed) direction for transparency. Item numbers follow the questionnaire numbering.

No	Item (AIDI Statement)	Mean	SD
9	I rely on free AI tools to complete most of my academic tasks.	2.92	0.91
10	I feel uncomfortable working on assignments without using AI tools.	2.73	0.91
11	I use AI tools even for simple academic tasks I can do on my own.	2.49	1.05
12	AI tools help me finish tasks faster than doing them independently.	3.41	1.03
13	I depend on AI-generated explanations instead of studying course materials.	2.83	0.93
14	I rely on AI tools to generate ideas for my academic work.	2.94	0.97
15	Without AI tools, I feel my academic performance would decline.	2.59	0.97
16	I use AI tools as a substitute for my own thinking.	2.64	0.98
17	I rely on AI tools to solve programming problems for me.	2.96	0.94
18	I check and understand AI-generated outputs before submitting them.	3.29	1.04
19	I feel confident completing academic tasks without AI assistance.	3.25	0.94
20	AI tools have become an essential part of my academic routine.	3.06	0.88
21	I struggle to complete tasks when AI tools are not allowed.	2.59	0.91
22	I rely more on AI tools than my own skills when studying.	2.46	1.00
23	I believe I may be too dependent on AI tools for my studies.	2.63	1.10

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Table 7. Overall AI Dependency Level

Mean Score Range	Interpretation	Frequency (f)	Percentage (%)
1.00 – 2.60	Low Dependency	74	44.0
2.61 – 3.40	Moderate Dependency	76	45.2
3.41 – 5.00	High Dependency	18	10.7

Table 8. Academic-Related Factors: Study Habits

Note. Study Habits had 4 items reported as three SRL indicators (two single-item); regression used the 4-item mean.

Indicator	Mean	SD	Interpretation
Planning and Goal Setting	3.45	0.78	Satisfactory
Monitoring Learning Progress	3.22	0.85	Satisfactory
Independent Problem Solving	3.12	0.92	Satisfactory

Table 9. Awareness of and Compliance with the Institutional AI Use Policy (n = 168)

Note. For Table 11, policy-unaware respondents were coded as the lowest policy compliance level.

Panel A. Policy Awareness

Indicator	Category	Frequency (f)	Percentage (%)
Awareness of AI Policy	Yes	147	87.5
	No	21	12.5

Panel B. Perceived Policy Compliance (overall)

Indicator	Category	Frequency (f)	Percentage (%)
Perceived Compliance	High/Moderate	142	84.5
	Low / Unaware	26	15.5

Table 10. t-Test Results: AI Dependency by Policy Awareness

Group	N	Mean (AIDI)	SD	t(166)	p
Aware of Policy	147	2.75	0.54	−2.25	.026
Unaware of Policy	21	3.04	0.66		

Table 11. Multiple Regression Analysis Predicting AI Dependency (AIDI)

Panel A. Model Summary

N	Predictors (k)	R^2	Adjusted R^2	F (df1, df2)	p (Model)
168	3	0.092	0.075	5.54 (3, 164)	.001

Panel B. Regression Coefficients

Predictor	B	SE B	β	t	p
Constant	4.483	1.037	—	4.324	< .001
Policy Compliance	−0.137	0.038	−0.290	−3.620	< .001
Study Habits	0.060	0.051	0.088	1.170	.246
GWA	−0.017	0.012	−0.104	−1.384	.168

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