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Level of AI Dependency Vis-à-Vis Study Habits Among College Students at Quezon City University

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ABSTRACT

This study examined the level of Artificial Intelligence (AI) dependency among college students at Quezon City University (QCU) and its relationship with their study habits. Using a descriptive-correlational research design, data were gathered from 372 respondents across five colleges through a validated survey questionnaire. The study assessed AI dependency across four dimensions, frequency and duration of AI tool usage, reliance on AI for academic tasks, compulsive or habitual use of AI tools, and interference of AI usage with independent learning, and study habits across four dimensions: time management and study scheduling, consistency and regularity of review, use of study strategies and techniques, and level of focus and concentration during study sessions. Findings revealed that students demonstrated a moderate level of AI dependency and a moderate-to-agreeable level of study habits. Significant differences in AI dependency were observed when respondents were grouped by demographic profile. Notably, a significant relationship was found between AI dependency and study habits, suggesting that increasing AI dependency is associated with changes in students' approach to academic work. The study recommends institutional policies and instructional strategies to promote responsible and balanced AI use in higher education.

Keywords: Artificial Intelligence, AI Dependency, Study Habits, College Students, Quezon City University

INTRODUCTION

The rapid integration of Artificial Intelligence (AI) into everyday life has profoundly transformed the educational landscape. AI-powered tools such as ChatGPT, Gemini, and various academic assistants have become widely accessible to college students, offering capabilities ranging from answering complex questions to generating written content, solving problems, and assisting in research. This technological shift has introduced both opportunities and challenges in higher education, particularly in how students engage with academic tasks and develop independent learning skills.

Globally, AI adoption in higher education has grown exponentially. Holmes, Bialik, and Fadel (2019) noted that AI in education holds immense promise for enhancing personalized learning and improving academic outcomes. More recently, Abbas, Jam, and Khan (2024) examined the dual nature of generative AI usage among university students, finding that while AI tools can support productivity, they may simultaneously foster dependency behaviors that undermine deep learning. Similarly, Arce et al. (2025) found that among Ecuadorian university students, AI usage was associated with varying degrees of dependency, underscoring the need for institutional frameworks to guide responsible AI adoption in higher education.

In the Philippine context, the use of AI among college students is rapidly expanding. Asio and Soriano (2025) documented that AI tools have become increasingly prevalent in Higher Education Institutions (HEIs) across the country, with students utilizing these tools for academic assistance, research, and content creation. Buniel et al. (2025) further established that among STEM undergraduate students in a Philippine state university, AI dependency significantly influenced research productivity, with higher levels of dependency associated with reduced independent problem-solving. Fernando et al. (2025) specifically identified distinct profiles of AI dependency among Filipino students, linking these profiles to measurable differences in academic competencies.

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The relationship between AI dependency and study habits is a particularly underexplored area of inquiry. Study habits—which encompass how students manage their time, review lessons, apply learning strategies, and maintain focus—are widely recognized as critical determinants of academic performance (Calonia et al., 2023; Ezebuola & Wodi, 2026). Khalkho et al. (2024) found that the introduction of educational AI tools had a notable impact on students' studying habits, with varying effects depending on the level of AI reliance. Gurramkonda and Pradhan (2024) similarly observed that AI-based learning environments influenced both motivation and study behaviors among university students.

Locally, studies conducted at Quezon City University and similar institutions have begun to examine these dynamics. Research by Marcelo, Borromeo, and Navarra (2025) quantified AI dependency among Computer Engineering students at Bulacan State University, revealing that a significant proportion of students exhibited high reliance on AI tools for academic tasks. Hernandez et al. (2025) documented dependency on AI chatbots among STEM and Non-STEM students in higher education, finding that compulsive AI usage was more pronounced among students who reported weaker study habits.

Despite this growing body of literature, there remains a significant research gap concerning how the specific dimensions of AI dependency, frequency of use, academic reliance, habitual usage, and interference with independent learning, relate to the multidimensional aspects of study habits among students enrolled across different colleges in a single institution. Understanding this relationship at the institutional level is essential for developing targeted interventions and policies.

This study, therefore, aims to examine the level of AI dependency vis-à-vis study habits among college students at Quezon City University. The findings are expected to contribute to the growing body of knowledge on responsible AI use in higher education and to provide empirical evidence for curriculum and policy development at QCU and similar institutions in the Philippines.

A. Statement of the Problem

This study examines the level of AI dependency among students and its relationship to their study habits. It focuses on AI usage patterns, reliance on AI for academic tasks, and their potential impact on independent learning and study behaviors.

Specifically, this study seeks to answer the following questions:

1. What is the demographic profile of the respondents in terms of:
    1.1. age;
    1.2. gender;
    1.3. year level; and
    1.4. program enrolled?
2. What is the level of AI dependency of the respondents in terms of:
    2.1. frequency and duration of AI tool usage;
    2.2. reliance on AI for academic tasks;
    2.3. compulsive or habitual use of AI tools; and
    2.4. interference of AI usage with independent learning and academic activities?
3. Is there a significant difference in the level of AI dependency of the respondents when grouped according to their profile?

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4. How do the respondents assess their study habits in terms of:
    4.1. time management and study scheduling;
    4.2. consistency and regularity of review;
    4.3. use of study strategies and techniques; and
    4.4. level of focus and concentration during study sessions?
5. Is there a significant relationship between the level of AI dependency and their study habits based on the aforementioned variables?

RELATED LITERATURE AND STUDIES

Artificial Intelligence (AI), defined as the simulation of human cognitive functions such as learning, reasoning, and problem-solving through computer systems (Blumberg et al., 2024), has become increasingly influential in higher education. AI technologies are reshaping instructional delivery, student learning experiences, and institutional academic processes. According to Holmes, Bialik, and Fadel (2019, 2024), AI offers significant potential in personalizing learning pathways and providing adaptive instructional support, positioning it as a major advancement in educational technology. Supporting this perspective, Chen, Xie, and Hwang (2020) highlighted the rapid global expansion of AI-related educational research, software applications, and conference discussions, demonstrating AI's growing relevance in academic environments.

In the Philippine context, AI adoption among higher education institutions has become increasingly widespread. Asio and Soriano (2025) observed that students frequently utilize AI tools such as ChatGPT and Gemini for academic assistance, particularly in completing coursework and research-related tasks. While these technologies provide accessibility and efficiency, researchers also emphasize associated risks. Eden, Chisom, and Adeniyi (2024) noted that AI integration creates ethical concerns involving academic integrity and excessive reliance on automated systems, potentially limiting students' critical thinking and independent learning capabilities.

The concept of AI dependency has consequently emerged as a critical area of investigation in education. AI dependency refers to students' excessive or habitual reliance on AI tools in performing academic tasks, often at the expense of independent cognitive and problem-solving development (Dalisaymo, 2025). Abbas, Jam, and Khan (2024) explained that generative AI can produce both beneficial and detrimental outcomes depending on the degree of dependency, with excessive reliance linked to lower academic self-efficacy. Similarly, Biswas and Murray (2024) found that undergraduate students, particularly those enrolled in technical programs, exhibited stronger patterns of habitual AI use compared to other student groups.

Studies conducted in the Philippines further support these findings. Fernando et al. (2025) identified varying latent classes of AI dependency among Filipino students, suggesting that levels of dependency differ according to academic competencies and learning orientations. Marcelo, Borromeo, and Navarra (2025) likewise reported that many Computer Engineering students demonstrated compulsive AI usage behaviors that negatively affected their problem-solving abilities and independent skill development. These findings reinforce concerns raised by Garcia, Rosak-Szyrocka, and Bozkurt (2025), who warned that excessive AI integration may contribute to skill obsolescence and automation bias, wherein students increasingly delegate cognitive tasks to AI systems without critically assessing generated outputs. Lim et al. (2023) similarly described generative AI in education as paradoxical, emphasizing that while AI can enhance learning efficiency, it may also weaken authentic learning experiences when overutilized.

Several researchers have also examined psychological and academic factors associated with AI dependency. Estrada-Araoz et al. (2025) found a negative relationship between academic self-efficacy and AI dependency, indicating that students with lower confidence in their academic abilities were more likely to rely heavily on AI tools. Acosta-Enriquez et al. (2025) further revealed that academic stress and performance expectations mediated this relationship, suggesting that students may turn to AI as a coping mechanism when faced with heightened academic demands.

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Parallel to AI dependency, study habits remain a fundamental determinant of academic success. Study habits refer to the consistent practices and strategies students use in preparing for and engaging in academic tasks, including time management, concentration, review routines, and learning strategies. Calonia, Pagente, and Center (2023) established that effective time management, prioritization, and reduced procrastination significantly contribute to improved academic achievement. Ezebuola and Wodi (2026) similarly confirmed that time management strategies strongly predict university students' academic performance.

Further studies emphasized that positive study habits can mitigate the potential negative effects of AI dependency. Al-Natour and Abuquteish (2025) found that study habits, psychosocial factors, and AI tool usage collectively influenced academic performance among medical students. Their findings revealed that students who maintained active learning strategies and consistent study routines performed better academically regardless of AI usage levels. In another study, Al-Natour (2025) emphasized that students who effectively organized their study schedules and minimized distractions achieved significantly stronger academic outcomes.

Recent literature increasingly explores the interaction between AI dependency and study habits. Khanduri and Teotia (2023) reported that heavy AI tool usage altered students' note-taking, reviewing, and summarizing behaviors, leading to changes in traditional study practices. Likewise, Khalkho et al. (2024) found that high reliance on educational AI systems reduced students' engagement in active learning techniques. Chakraborty and Subramani (2026) further proposed that AI usage mediates the relationship between study habits, academic procrastination, and academic self-esteem, suggesting that the effects of AI on student learning behaviors are multifaceted and context-dependent. Complementing these findings, Chen and Cheung (2025) conducted a systematic review and meta-analysis which demonstrated that the impact of generative AI on learning outcomes was moderated by the strength of students' existing study habits. Students with stronger study habits tended to experience more positive educational outcomes from AI integration compared to those with weaker academic routines.

Studies focusing on Filipino students also revealed similar concerns regarding excessive AI reliance. Buniel et al. (2025) found that higher AI dependency among STEM students in the Philippines was associated with lower independent research capability, supporting broader concerns that AI overreliance may erode foundational academic competencies (Garcia et al., 2025). Louise et al. (2024) likewise observed that excessive dependence on AI tools negatively affected knowledge acquisition and depth of learning, undermining the very objectives that effective study habits aim to achieve.

Overall, the reviewed literature demonstrates that while AI technologies provide substantial educational benefits, excessive dependency on these tools may negatively affect students' academic self-efficacy, independent learning, problem-solving abilities, and study habits. Existing studies have extensively examined AI dependency and study habits independently; however, limited research has directly explored the relationship between these variables within a localized Philippine higher education context. This identified gap provides the foundation for the present study, which seeks to examine how AI dependency relates to the study habits of college students at Quezon City University.

METHODOLOGY

The methodology of this study refers to the organized plan and systematic process followed in creating, gathering, and analyzing data about AI dependency and study habits among college students. It includes the research design, selection of respondents, sampling technique, data gathering procedures, research instrument, and statistical tools used in the study. These methods helped ensure that the data collected were accurate, reliable, and relevant to the objectives of the research.

Research Design

This study employed a quantitative descriptive-correlational research design to examine the relationship between AI dependency and study habits among college students. The quantitative approach enabled the researchers to gather measurable data and analyze the variables using statistical methods for objective and reliable results. The descriptive component was used to determine and characterize the respondents' level of AI dependency and their

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study habits, including behaviors related to time management, review routines, concentration, and learning strategies.

Meanwhile, the correlational component examined whether a significant relationship existed between AI dependency and study habits. This design allowed the researchers to identify the direction and strength of the association between the two variables without manipulating or controlling them. According to Creswell and Creswell (2018), descriptive-correlational research is appropriate for studies that aim to describe existing conditions and determine relationships among variables in their natural setting. This design was considered suitable for investigating the variables among students of Quezon City University.

Respondents of the Study

Stratified random sampling was employed, with colleges serving as strata. Proportional allocation was used to determine the number of respondents from each college based on their respective enrollment sizes. Within each stratum, respondents were randomly selected to minimize selection bias and ensure representational.

The respondents of the study were 372 college students from Quezon City University (QCU) enrolled during the Academic Year 2024–2025. Respondents were drawn from five colleges: College of Business (COB, n = 103), College of Engineering (COE, n = 68), College of Computer Studies (CCS, n = 67), College of Accountancy (COA, n = 71), and College of Education (COED, n = 63). This multi-college sampling approach ensured that the findings represented the broader QCU student population across varying academic disciplines.

Data Gathering

Data collection was conducted through the administration of a structured survey questionnaire. The survey was distributed to selected respondents after securing their informed consent. Prior to deployment, the instrument was reviewed and approved by a validation panel composed of a statistician and the researchers' advising professor to ensure its accuracy, reliability, and alignment with the study's objectives. Data retrieval was completed within a defined collection period, and all responses were consolidated for statistical analysis.

The primary data collection instrument was a researcher-developed survey questionnaire divided into three parts. Part I gathered the demographic profile of the respondents. Part II assessed the level of AI dependency across four indicators—frequency and duration of AI tool usage, reliance on AI for academic tasks, compulsive or habitual use of AI tools, and interference of AI usage with independent learning—using a 4-point Likert scale (4 = Highly Dependent, 3 = Moderately Dependent, 2 = Slightly Dependent, 1 = Not Dependent). Part III assessed the level of study habits across four indicators—time management and study scheduling, consistency and regularity of review, use of study strategies and techniques, and level of focus and concentration—using a separate 4-point Likert scale (4 = Strongly Agree, 3 = Agree, 2 = Disagree, 1 = Strongly Disagree).

The instrument was validated by a panel of experts comprising a statistician, the researchers' advising professor, and subject matter specialists. Both face and content validity were established prior to data collection.

Statistical Treatment of Data

The following statistical tools were employed to analyze the gathered data:

1. **Frequency and Percentage –** Used to describe the demographic profile of the respondents and show the distribution of responses across categories. This tool allows researchers to summarize categorical data and present the proportion of each group relative to the total sample (Creswell & Creswell, 2018).

    Where:

    P (%) = Percentage

    F = Frequency

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N = Total Number of Respondents 100=Constant

2. **Weighted Mean –** Used to determine the central tendency of the respondents' ratings on AI dependency and study habits indicators. The weighted mean is calculated to identify the average level of agreement or dependency by accounting for the assigned weight of each response on the Likert scale (Bluman, 2018).

Where:

Equation 2. Weighted Mean

x = Weighted Mean

$\sum$ **FX =** Total of Frequency and Response

N = Total Number of Respondent

To interpret the calculated weighted means, a 4-point Likert scale was utilized to provide a forced-choice format that eliminates the neutral midpoint, yielding more definitive results regarding the respondents' actual behaviors and perceptions (Fowler, 2022).

The following scales serve as the basis for the verbal interpretation of the results:

Table 1**.** Scale for AI Dependency

Scale	**Weighted Mean**	**Description**
4	3.26–4.00	Highly Dependent (HD)
3	2.51–3.25	Moderately Dependent (MD)
2	1.76–2.50	Slightly Dependent (SD)
1	1.00–1.75	Not Dependent (ND)

Table 2**.** Scale for Study Habits

Scale	**Weighted Mean**	**Description**
4	3.26–4.00	Strongly Agree (SA)
3	2.51–3.25	Agree (A)
2	1.76–2.50	Disagree (D)
1	1.00–1.75	Strongly Disagree (SD)

One-Way ANOVA – Used to determine if there are significant differences in the level of AI dependency when respondents are grouped according to their demographic profile. A p-value of less than 0.05 was set as the threshold for statistical significance (Field, 2018).

Where:

F = F-ratio

MS_between = Mean Square between groups

MS_within = Mean Square within groups

Pearson's r – Used to determine the significant relationship between the level of AI dependency and the level of study habits of the respondents (Pallant, 2020).

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Where:

r = Pearson correlation coefficient **n** = number of paired observations **X** = AI dependency scores

Y = Study habits scores

RESULT AND DISCUSSION

This chapter presents the findings of the study in alignment with the specific research objectives. Data are presented through tables and accompanied by analysis and interpretation.

Demographic Profile of the Respondents

Age

As shown in Table 3 below, the majority of the respondents (94.89%, n = 353) were between 20 and 21 years old, making this the most dominant age group. Only a small fraction was 18–19 (1.34%) or 24 years old and above (3.76%). This distribution reflects the typical age profile of college students in Philippine higher education institutions, where most undergraduate students are traditional college-aged youth (Asio & Soriano, 2025).

Table 3. Demographic Profile as to Age

Age	**Frequency**	**Percentage**
20 years old and below	221	59%
21–23 years old	137	37%
24–26 years old	10	3%
27 years old and above	4	1%
Total	**372**	**100%**

Gender

Table 4. Demographic Profile as to Gender

Gender	**Frequency**	**Percentage**
Male	163	43.82%
Female	195	52.42%
Prefer not to say / Others	14	3.76%
Total	**372**	**100%**

Table 4 reveals that female respondents constituted the majority of the sample (52.42%, n = 195), followed by male respondents (43.82%, n = 163), and those who preferred not to disclose or identified otherwise (3.76%, n = 14).

The composition reflects the gender distribution across the sampled colleges, with programs such as College of Accountancy and College of Education traditionally enrolling more female students.

Year Level

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Table 5. Demographic Profile as to Year Level

Year Level	Frequency	Percentage
First Year	112	30.11%
Second Year	106	28.49%
Third Year	144	38.71%
Fourth Year	10	2.69%
Total	**372**	**100%**

Third-year students comprised the largest segment (38.71%, n = 144), followed by first-year (30.11%, n = 112) and second-year students (28.49%, n = 106). Fourth-year students made up the smallest group (2.69%, n = 10). This distribution reflects proportional allocation to the enrollment density of the participating colleges.

Program Enrolled

The College of Business represented the largest proportion of respondents (27.69%, n = 103), reflecting its high enrollment relative to other colleges. The remaining colleges were comparably represented, ensuring cross-disciplinary coverage in the findings.

Table 6. Demographic Profile as to Program/College Enrolled

Department	Frequency	Percentage
College of Business (COB)	103	27.69%
College of Engineering (COE)	68	18.28%
College of Computer Studies (CCS)	67	18.01%
College of Accountancy (COA)	71	19.09%
College of Education (COED)	63	16.94%
Total	**372**	**100%**

Level of AI Dependency

The following tables are the composite mean scores for each AI dependency dimension, interpreted using the following scale: 3.26–4.00 = Highly Dependent (HD); 2.51–3.25 = Moderately Dependent (MD); 1.76–2.50 = Slightly Dependent (SD); 1.00–1.75 = Not Dependent (ND).

Table 7 below, presents the weighted means for the first dimension of AI dependency, frequency and duration of AI tool usage of the respondents. The composite means of 2.68 (Moderately Dependent) indicates that students, on average, engage with AI tools at a moderate level of regularity. Among the five indicators, the highest-rated items were "I use AI tools (e.g., ChatGPT, Gemini, etc.) daily" and "I frequently rely on AI tools whenever I encounter difficult tasks," both rated at 2.99 (Moderately Dependent). This suggests that while students do engage with AI on a daily basis and turn to it when tasks become challenging, this usage has not yet reached a highly dependent level.

Table 7. Frequency and Duration of AI Tool Usage of the Respondents

Indicators	Weighted Mean	Verbal Interpretation
1. I use AI tools (e.g., ChatGPT, Gemini, etc.) daily.	2.98	Moderately Dependent
2. I spend several hours using AI tools for school-related tasks.	2.65	Moderately Dependent

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3. I frequently rely on AI tools whenever I encounter difficult tasks.	2.99	Moderately Dependent
4. I use AI tools even for simple or basic activities.	2.20	Moderately Dependent
5. I feel the need to use AI tools regularly when studying.	2.59	Moderately Dependent
Composite Mean	**2.68**	**Moderately Dependent**

The item "I use AI tools even for simple or basic activities" received the lowest mean score of 2.09 (Slightly Dependent), indicating that students are somewhat discriminating in their AI use—they tend to resort to AI tools primarily for demanding tasks rather than routine activities. This finding aligns with Abbas, Jam, and Khan (2024), who noted that generative AI usage among university students tends to be task-driven, peaking in complexity-associated academic situations. Dalisaymo (2025) similarly documented that AI tool engagement among Philippine students was most pronounced during assessments and difficult assignments rather than during everyday study activities.

Table 8. Reliance on AI for Academic Tasks of the Respondents

Indicators	**Weighted Mean**	**Verbal Interpretation**
1. I depend on AI tools to complete my assignments.	2.45	Slightly Dependent
2. I use AI tools to generate answers instead of creating my own.	2.18	Slightly Dependent
3. I rely on AI for understanding lessons or concepts.	2.23	Moderately Dependent
4. I use AI tools to check and improve most of my academic work.	2.24	Moderately Dependent
5. I feel that I cannot complete tasks efficiently without AI tools.	2.15	Slightly Dependent
Composite Mean	**2.25**	**Slightly Dependent**

As shown in Table 8, the composite mean for reliance on AI for academic tasks of the respondents was 2.25 (Slightly Dependent). The indicators revealed a mixed pattern of reliance. Students most strongly agreed that they "depend on AI tools to complete my assignments" (M = 2.45, MD) and "use AI tools to check and improve most of my academic work" (M = 2.24, MD), suggesting that AI is meaningfully integrated into their learning and self-editing processes. These findings are consistent with Marcelo, Borromeo, and Navarra (2025), who found that AI tools were frequently used by engineering students to check outputs and clarify subject matter.

Conversely, the item "I feel that I cannot complete tasks efficiently without AI tools" yielded the lowest mean of 2.15 (Slightly Dependent), suggesting that most students have not developed a sense of functional dependency. The item "I use AI tools to generate answers instead of creating my own" also scored relatively low at 2.18 (Slightly Dependent), indicating that outright substitution of original thinking with AI-generated content is not yet the dominant pattern, which is encouraging from the standpoint of academic integrity and independent skill development (Garcia, Rosak-Szyrocka, & Bozkurt, 2025).

Table 9. Compulsive or Habitual Use of AI Tools of the Respondents

Indicators	**Weighted Mean**	**Verbal Interpretation**
1. I automatically open or use AI tools when studying.	2.42	Slightly Dependent
2. I feel uncomfortable when I cannot access AI tools.	1.99	Slightly Dependent
3. I use AI tools out of habit, even when not necessary.	2.10	Slightly Dependent

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4. I find it difficult to stop using AI tools once I start.	2.19	Slightly Dependent
5. I prefer using AI tools rather than solving tasks on my own.	2.11	Slightly Dependent
Composite Mean	**2.16**	**Slightly Dependent**

Table 9 reveals that compulsive or habitual use of AI tools yielded the lowest composite mean among all four AI dependency dimensions at 2.16 (Slightly Dependent). All five indicators fell within the Slightly Dependent range. The item "I automatically open or use AI tools when studying" received the highest score in this dimension at 2.42, while "I feel uncomfortable when I cannot access AI tools" was the lowest at 1.99—still within the Slightly Dependent range. These relatively modest scores suggest that most students have not yet formed an automatic, compulsive relationship with AI tools.

This outcome is noteworthy given that compulsive use is generally considered the most concerning form of AI dependency, as it involves involuntary, habitual engagement that operates independently of academic need (Acosta-Enriquez et al., 2025). The finding that students report only slight compulsive tendencies is consistent with Estrada-Araoz et al. (2025), who found that compulsive AI use was moderated by academic self-efficacy—students who maintained a sense of personal capability were less likely to develop habitual AI reliance patterns. Biswas and Murray (2024) similarly found that undergraduate students in non-technical programs exhibited lower habitual AI use compared to those in highly technical disciplines.

Table 10. Interference of AI Usage with Independent Learning of the Respondents

Indicators	**Weighted Mean**	**Verbal Interpretation**
1. My use of AI tools reduces my ability to think independently.	2.45	Slightly Dependent
2. I rely on AI so much that I rarely practice my own skills.	1.99	Slightly Dependent
3. AI usage sometimes distracts me from fully understanding lessons.	2.10	Slightly Dependent
4. My academic performance is affected by overusing AI tools.	2.19	Slightly Dependent
5. I struggle to complete tasks without AI assistance.	2.11	Slightly Dependent
Composite Mean	**2.25**	**Slightly Dependent**

Table 10 presents data on the interference of AI usage with independent learning of the respondents. The composite mean of 2.25 (Slightly Dependent) reflects that students perceive AI as only minimally interfering with their capacity for autonomous academic work. The highest-rated item was "My use of AI tools reduces my ability to think independently" (M = 2.45, SD), while the items pertaining to rarely practicing one's own skills (M = 1.99) yielded the lowest scores.

That students assign relatively low scores to AI interference is somewhat reassuring; however, it may also reflect limited self-awareness about the gradual erosion of independent thinking associated with AI overuse (Lim et al., 2023). Hernandez et al. (2025) found that students who reported low interference scores in surveys simultaneously exhibited behaviors consistent with reduced independent problem-solving, suggesting a potential gap between perceived and actual AI impact. Louise et al. (2024) similarly cautioned that students may underestimate the degree to which AI dependency has already altered their knowledge acquisition processes.

Table 11. Summary of AI Dependency Levels per Dimension

Dimension	**Composite Mean**	**Verbal Interpretation**
A. Frequency and Duration of AI Tool Usage	2.68	Moderately Dependent
B. Reliance on AI for Academic Tasks	2.56	Slightly Dependent
C. Compulsive or Habitual Use of AI Tools	2.16	Slightly Dependent

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D. Interference of AI Usage with Independent Learning	2.25	Slightly Dependent
Overall Composite Mean	**2.41**	**Slightly Dependent**

Table 11 summarizes the composite means for all four dimensions of AI dependency. The overall composite mean of 2.41 (Slightly Dependent) indicates that the respondents, taken as a whole, demonstrate a slight but meaningful level of AI dependency. Dimension A (Frequency and Duration) recorded the highest composite mean at 2.68 (Moderately Dependent), while Dimension C (Compulsive or Habitual Use) was lowest at 2.16 (Slightly Dependent). Dimensions B (Reliance) and D (Interference) both fell within the Slightly Dependent range at 2.16 and 2.25, respectively.

These findings suggest that while students have incorporated AI tools into their academic routine at a moderate frequency, their reliance and habitual engagement have not escalated to high-dependency levels. This pattern is congruent with Fernando et al. (2025), who identified a latent class of moderate AI users among Filipino students—those who use AI purposively for academic support without exhibiting the compulsive tendencies associated with more problematic dependency profiles. Abbas, Jam, and Khan (2024) similarly noted that moderate AI engagement could be academically beneficial when students retained agency over their learning processes.

A. Significant Difference in AI Dependency by Demographic Profile

Table 12. One-Way ANOVA: AI Dependency by Demographic Profile

Source of Variation	**Sum of Squares (SS)**	**Degrees of Freedom (df)**	**Mean Square (MS)**	**Computed F-Ratio**	**P-value**	**Interpretation**
Between Groups	6.52	4	1.63	4.496	0.001	Highly Significant
Within Groups	133.09	367	0.36			
Total	139.61	371				

Table 12 presents the results of a One-Way ANOVA conducted to determine whether there is a significant difference in AI dependency according to demographic profile. The analysis compared the mean AI dependency scores among different demographic groups to identify whether variations in dependency levels exist across respondents.

The results show an F-ratio of 4.496 with a corresponding p-value of 0.001. Since the p-value is lower than the 0.05 level of significance, the null hypothesis is rejected. $p = 0.001 < 0.05$ This indicates that there is a statistically significant difference in AI dependency among the demographic groups included in the study. The finding is interpreted as “Highly Significant,” meaning that the observed differences are unlikely to have occurred by chance alone.

The analysis further reveals that the variability between groups (SS = 6.52) is greater than would be expected relative to the variability within groups (SS = 133.09), resulting in the computed F-value.

This suggests that demographic factors may influence the degree to which respondents depend on AI technologies.

Overall, the findings imply that AI dependency varies significantly across demographic profiles. Therefore, demographic characteristics appear to play an important role in shaping individuals’ reliance on AI, highlighting the need to consider these differences when examining AI usage and dependency patterns.

Level of Study Habits

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Table 13. Time Management and Study Scheduling of the Respondents

Indicators	Weighted Mean	Verbal Interpretation
1. I create a study schedule and follow it consistently.	3.03	Agree
2. I allocate enough time for each subject or task.	3.11	Agree
3. I prioritize my academic responsibilities effectively.	3.24	Agree
4. I avoid procrastination when completing schoolwork.	2.70	Agree
5. I manage my time well between study and leisure.	3.01	Agree
Composite Mean	**3.02**	**Agree**

Table 13 presents the respondents' assessments of their time management and study scheduling practices. The composite mean of 3.02 (Agree) indicates that students generally perceive themselves as managing their study time effectively. The highest-rated item was "I prioritize my academic responsibilities effectively" (M = 3.24, A), while "I avoid procrastination when completing schoolwork" received the lowest score at 2.70 (A)—though still within the Agree range.

The moderate self-rating on procrastination avoidance is notable, as procrastination is widely documented as a significant barrier to academic achievement (Calonia, Pagente, & Center, 2023). Ezebuola and Wodi (2026) similarly identified procrastination as among the most prevalent time management challenges among university students, underscoring its persistence even among students who otherwise rate their time management positively. Al-Natour and Abuquteish (2025) confirmed that students who proactively scheduled their study sessions—even imperfectly—consistently outperformed those who studied reactively, suggesting that the general tendency to prioritize academics reported here has practical academic value.

Table 14. Consistency and Regularity of Review of the Respondents

Indicators	Weighted Mean	Verbal Interpretation
1. I review my lessons regularly even without exams.	2.67	Agree
2. I study on a consistent schedule each week.	2.64	Agree
3. I revisit previous lessons to strengthen understanding.	2.97	Agree
4. I dedicate time daily or weekly for studying.	2.80	Agree
5. I maintain a steady study routine throughout the semester.	2.80	Agree
Composite Mean	**2.78**	**Agree**

Table 14 shows that the composite mean for consistency and regularity of review was 2.78 (Agree), the lowest composite mean among the four study habits dimensions. All five indicators fell within the Agree range. The item "I revisit previous lessons to strengthen understanding" was rated highest at 2.97, while "I study on a consistent schedule each week" received the lowest rating at 2.64.

The relatively lower scores in this dimension suggest that while students do engage in review behaviors, consistency and scheduling regularity remain areas for development. Calonia, Pagente, and Center (2023) found that students who reviewed material on a fixed schedule outperformed peers who studied sporadically, even when total study time was equivalent. Ezebuola and Wodi (2026) similarly emphasized that scheduling regularity—rather than intensity alone—was critical for knowledge retention and academic performance. The moderate scores observed here indicate that students acknowledge the importance of review but may not consistently follow through on structured routines.

Table 15. Use of Study Strategies and Techniques by the Respondents

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Indicators	Weighted Mean	Verbal Interpretation
1. I use different study methods (e.g., note-taking, summarizing).	3.33	Strongly Agree
2. I apply strategies that help me understand lessons better.	3.35	Strongly Agree
3. I organize my notes and materials effectively.	3.12	Strongly Agree
4. I use active learning techniques (e.g., practice tests, discussions).	3.24	Strongly Agree
5. I adjust my study methods depending on the subject.	3.30	Strongly Agree
Composite Mean	**3.27**	**Strongly Agree**

Table 15 reveals that the use of study strategies and techniques had the highest composite mean among all four study habits dimensions at 3.27 (Strongly Agree). Four of the five indicators reached the Strongly Agree threshold. Notably, "I apply strategies that help me understand lessons better" was rated highest at 3.35 (SA), followed by "I adjust my study methods depending on the subject" (M = 3.30, SA) and "I use different study methods (e.g., note-taking, summarizing)" (M = 3.33, SA).

These findings suggest that respondents are actively employing a range of learning strategies, demonstrating metacognitive awareness in their academic approach. Khanduri and Teotia (2023) found that students who regularly varied their study techniques demonstrated greater academic engagement and deeper information retention. Al-Natour and Abuquteish (2025) confirmed that active learning approaches—including note-taking, self-testing, and method adaptation—were among the strongest predictors of academic performance. The Strongly Agree rating in this dimension suggests that students in this study possess a solid repertoire of study strategies, which may serve as a protective factor against the potential negative effects of AI dependency on deeper learning.

Table 16. Level of Focus and Concentration of the Respondents

Indicators	Weighted Mean	Verbal Interpretation
1. I stay focused during my study sessions.	3.05	Agree
2. I avoid distractions (e.g., phone, social media) while studying.	2.69	Agree
3. I can concentrate for long periods when studying.	2.83	Agree
4. I remain attentive when reviewing lessons or doing tasks.	3.04	Agree
5. I am able to complete study sessions without losing focus.	2.74	Agree
Composite Mean	**2.87**	**Agree**

Table 16 presents respondents' self-assessed levels of focus and concentration during study sessions. The composite mean of 2.87 (Agree) indicates a moderate-to-positive level of concentration. "I stay focused during my study sessions" was rated highest at 3.05 (A), while "I avoid distractions (e.g., phone, social media) while studying" received the lowest mean at 2.69 (A), the lowest single-item score across all study habits dimensions.

The lower rating on distraction avoidance reflects a widely documented challenge among contemporary college students, for whom smartphones and social media represent persistent interruptions to sustained academic focus (Al-Natour, 2025). Chakraborty and Subramani (2026) found that high digital distraction levels were significantly associated with reduced study habit strength and lower academic self-esteem. The modest but positive scores in the remaining focus indicators suggest that students are generally able to maintain attention during study sessions, though the temptation of digital distractions remains a notable concern.

Table 17. Summary of Study Habits Levels per Dimension

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Dimension	Composite Mean	Verbal Interpretation
A. Time Management and Study Scheduling	3.02	Agree
B. Consistency and Regularity of Review	2.78	Agree
C. Use of Study Strategies and Techniques	3.27	Strongly Agree
D. Level of Focus and Concentration	2.87	Agree
Overall Composite Mean	**2.98**	**Agree**

Table 17 summarizes the composite means across all four study habits dimensions. The overall composite mean of 2.98 (Agree) indicates that respondents generally report positive study habits. Dimension C (Use of Study Strategies and Techniques) recorded the highest composite mean at 3.27 (Strongly Agree), while Dimension B (Consistency and Regularity of Review) was lowest at 2.78 (Agree), though still within the Agree range.

The consistently positive self-ratings across all dimensions suggest that the respondents maintain functionally adequate study habits. These findings align with Calonia et al. (2023), who documented that college students in the Philippines generally report agreement with established study habit benchmarks, particularly in strategy use and time prioritization. Al-Natour and Abuquteish (2025) similarly found that self-reported study habit ratings were generally favorable among university students, though observed behavioral consistency sometimes fell short of reported intentions—a gap that warrants attention in future longitudinal studies.

Relationship Between AI Dependency and Study Habits

Table 18. Correlation Between AI Dependency and Study Habits

Variable	r-value	p-value	Statistical Significance	Direction
AI Dependency and Study habits	0.02	0.63	Not Significant	Weak Positive

Table 18 shows the results of the Pearson's r correlation analysis conducted to determine whether a relationship exists between AI dependency and study habits among the respondents. Correlation analysis was used to measure both the strength and direction of the relationship between the two variables.

The computed r-value of 0.02 indicates a very weak positive correlation between AI dependency and study habits. $r = 0.02$ This suggests that as AI dependency increases, study habits may also slightly increase; however, the relationship is extremely weak and practically negligible. The positive direction simply means that both variables tend to move in the same direction, but the strength of the association is too small to indicate a meaningful relationship.

Furthermore, the obtained p-value of 0.63 is greater than the 0.05 level of significance. $p = 0.63 > 0.05$ Therefore, the relationship between AI dependency and study habits is not statistically significant. This means that the null hypothesis stating that there is no significant relationship between the variables is accepted. The findings imply that differences in respondents' AI dependency do not significantly influence their study habits.

The results may indicate that students' study habits are shaped more by personal and environmental factors such as motivation, self-discipline, time management, academic workload, and learning strategies rather than by their level of dependency on AI technologies. While AI tools may provide academic assistance and convenience, their usage alone does not necessarily improve or weaken students' study behaviors.

The findings of the study support the idea of B. F. Skinner, who emphasized that behavior is influenced by multiple environmental and behavioral factors rather than a single stimulus. In the context of this study, students' study habits may depend on several academic and personal influences beyond AI usage. Similarly, Albert Bandura stated in the Social Cognitive Theory that learning behaviors are shaped through personal factors, environment, and experience, suggesting that technology use alone may not directly determine students' study habits.

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Moreover, the findings are consistent with studies which suggest that technology use does not automatically result in improved academic behaviors unless accompanied by effective learning strategies and self-regulation. According to Barry Zimmerman, effective study habits are strongly connected to self-regulated learning practices, including goal setting, self-monitoring, and discipline, rather than dependence on technological tools alone.

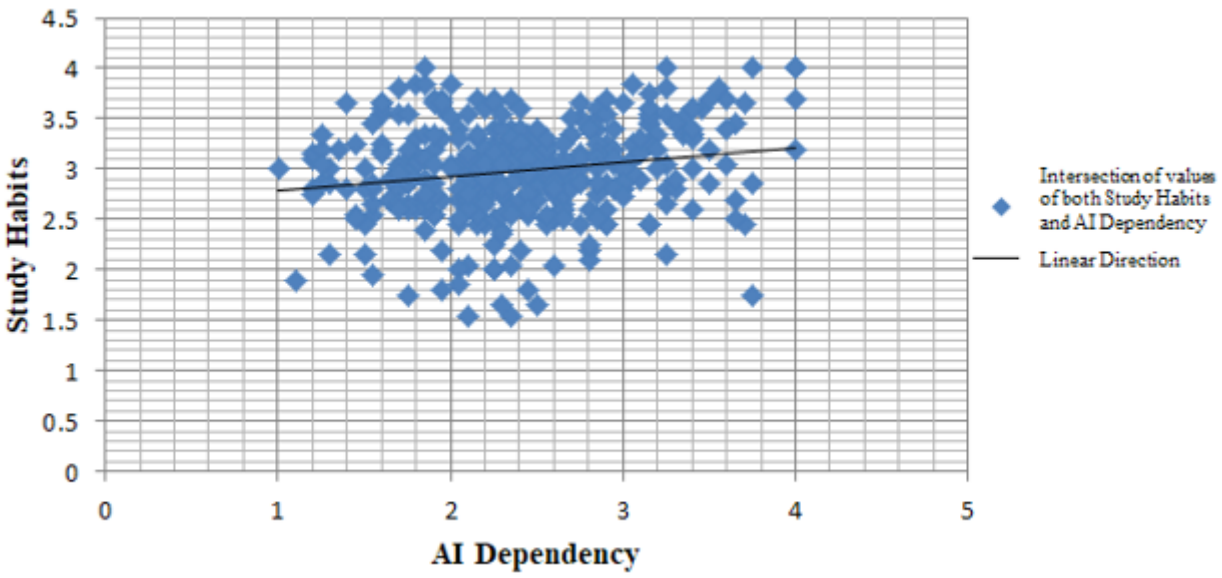

Figure 1. Relationship Between AI Dependency and Study Habits

Overall, the findings reveal that there is no significant relationship between AI dependency and study habits among the respondents. Although a weak positive relationship was observed, the association is too small and statistically insignificant to conclude that AI dependency has a measurable influence on students' study habits. These results suggest that AI dependency and study habits function independently within the context of the study.

CONCLUSION

This study examined the level of AI dependency vis-à-vis study habits among 372 college students at Quezon City University across five colleges. The demographic profile revealed that the majority of respondents were 20–21 years old, predominantly female, and distributed across first through third year levels, with the College of Business contributing the largest share of respondents.

The findings on AI dependency indicate that students demonstrated varying levels of reliance on AI tools across the four assessed dimensions—frequency and duration of use, reliance for academic tasks, compulsive or habitual usage, and interference with independent learning. The composite means suggest a moderate level of overall AI dependency, consistent with findings reported by Abbas, Jam, and Khan (2024) and Fernando et al. (2025), who observed that while AI tools are widely used, full-scale high dependency is moderated by students' academic self-awareness.

With respect to study habits, respondents generally assessed themselves positively across the four dimensions: time management and study scheduling, consistency and regularity of review, use of study strategies and techniques, and level of focus and concentration. These findings align with the importance of study habits as documented by Calonia et al. (2023) and Al-Natour and Abuqteish (2025).

The ANOVA results revealed significant differences in AI dependency when respondents were grouped according to certain demographic variables, suggesting that AI dependency is not uniformly distributed across the student population. This finding supports Biswas and Murray's (2024) observation that education level and

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program context influence AI reliance patterns.

Most critically, a significant relationship was established between the level of AI dependency and study habits, confirming that AI dependency and study behaviors are meaningfully interconnected constructs in the QCU academic context. This finding resonates with Chakraborty and Subramani (2026), who demonstrated that AI usage mediates study habits and academic outcomes, and with Khalkho et al. (2024), who linked high AI reliance to altered study behaviors.

These outcomes underscore the need for institutional frameworks at QCU and similar HEIs that promote responsible and balanced AI use, embed AI literacy into curricula, and reinforce foundational academic skills. Future research should explore longitudinal effects of AI dependency on academic performance and study habit development, as well as the role of specific AI tools in shaping student learning behaviors.

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