ARTIFICIAL INTELLIGENCE AND PSYCHOLOGICAL WELL-BEING AMONG UNIVERSITY STUDENTS

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Abstract:

Artificial Intelligence (AI) is now widely used by university students for academic purposes, but its relationship with psychological well-being is not yet well understood. This study examined that relationship among 300 university students using two validated tools: the Academic AI Usage Scale (AAIUS; Chakraborty & Subramani, 2025) and the Psychological Well-Being Scale (PWBS-SDCP; Sisodia & Choudhary, 2012). As primary data collection across the participating institutions is still in progress, the results reported here are based on a calibrated illustrative dataset built to reflect realistic patterns from published research, and should be read as a preview of the planned analysis rather than confirmed findings. In this illustrative analysis, students with higher overall AI usage reported significantly higher psychological well-being than students with lower usage, $t(292) = 3.92$, $p < .001$, $d = 0.45$. A closer look showed that this difference was mainly linked to using AI for academic support and skill-building, while AI dependence (relying on AI output without checking it) was not related to well-being. The findings suggest that how students use AI may matter more than how much they use it, with practical implications for AI literacy and student support in higher education.

1. Introduction:

Artificial Intelligence has become part of everyday academic life for university students, who now use AI tools for searching information, writing, and organising their coursework. Recent surveys show that AI use among students, particularly ChatGPT and similar tools, is now common rather than exceptional (Abdaljaleel et al., 2024; Sallam et al., 2023). While these tools can make academic tasks faster and easier, it is less clear how they relate to students' psychological well-being — their overall sense of satisfaction, effectiveness, and mental health.

Existing research suggests the answer may depend on how AI is used rather than simply how much. Studies show that AI can support learning when used to clarify concepts, get feedback, or organise ideas (Lin & Chen, 2024; Vieriu & Petrea, 2025). At the same time, other research warns that relying on AI without checking or thinking critically about its output — a pattern often called "AI dependence" — is linked to lower confidence and weaker independent thinking (Zhai et al., 2024; Zhang et al., 2024). This distinction is now measurable: the Academic AI Usage Scale (AAIUS) developed by Chakraborty and Subramani (2025) separates AI use into three types — Dependence, Academic Support, and Academic Skills — which allows researchers to ask a more precise question than "does AI use help or harm well-being?"

This study asks that more precise question: does overall AI usage relate to psychological well-being among university students, and do different types of AI use relate to well-being differently?

2. Review of Related Literature

AI adoption among students is widespread across countries and disciplines (Abdaljaleel et al., 2024; Sallam et al., 2023), and India's higher-education sector shows similarly fast but uneven adoption (Sharma et al., 2024). Several studies point to real academic benefits of AI use: it can support comprehension, provide quick feedback, and help students manage academic workload (Gruenhagen et al., 2024; Vieriu & Petrea, 2025). Wang and Wang (2024) found that Chinese college students' academic engagement related to better mental health partly through positive attitudes toward AI, while Lin and Chen (2024) found AI-integrated learning tools were linked to more positive academic emotions.

At the same time, a separate body of research raises concerns about over-reliance. Zhang et al. (2024) found that academic stress and pressure to perform predicted "problematic" AI usage patterns, and a systematic review by Zhai et al. (2024) concluded that over-reliance on AI tools is associated with weaker independent thinking. This concern echoes older research on cognitive offloading, which shows that outsourcing thinking to a tool can be helpful in moderation but can weaken skills and confidence when it replaces effort rather than supporting it (Risko & Gilbert, 2016).

Taken together, this literature suggests that "AI use" should not be treated as one single thing. This study follows that reasoning by looking at both students' overall AI usage and, more specifically, the three usage patterns identified by the AAIUS — Dependence, Academic Support, and Academic Skills — in relation to psychological well-being. Self-Determination Theory (Ryan & Deci, 2000), which holds that well-being depends on feeling capable and self-directed, offers a simple explanation for why these patterns might differ: AI use that builds a student's own skills and understanding should support well-being, while AI use that replaces a student's own effort may not.

3. Objectives of the Study

- To examine the level of Artificial Intelligence use among university students.
- To assess the psychological well-being of university students.
- To compare psychological well-being between high and low AI users.
- To examine whether different types of AI use (dependence, academic support, academic skills) relate differently to psychological well-being.
- To discuss the educational and psychological implications of the findings.

4. Hypotheses

H_0: There is no significant difference in psychological well-being between high and low AI users.

H_1: There is a significant difference in psychological well-being between high and low AI users.

In addition to this main comparison, the study also explores, on an exploratory basis, whether the three AAIUS usage patterns (Dependence, Academic Support, Academic Skills) relate differently to well-being.

5. Methodology

5.1 Research Design

A quantitative, comparative research design was used, comparing high and low AI-user groups on psychological well-being using an independent-samples t-test. Correlations between AI-usage patterns and well-being were examined as a secondary analysis.

5.2 A Note on the Data Used in This Paper

Data collection across the participating institutions is still underway. The figures reported in Section 6 come from a calibrated illustrative dataset (N = 300), built to reflect realistic reliability and effect-size patterns from published research on these two instruments, rather than from completed data collection. This is stated openly here and in the Limitations section, and the results should be read as a preview of the planned analysis rather than confirmed findings; they will be replaced with real results once data collection is complete.

5.3 Sample

The planned sample consists of 300 university students across eight participating institutions, selected through purposive sampling to capture a range of disciplines, year levels, and residential situations. In the illustrative sample, ages ranged from 17 to 28 years (M = 22.62, SD = 3.59); 156 (52.0%) were male and 144 (48.0%) were female; 165 (55.0%) were Day Scholars and 135 (45.0%) were Hostellers. Table 1 shows the full breakdown.

Table 1

Sample Characteristics (N = 300)

Characteristic	Category	n (%)
Gender	Male	156 (52.0%)
	Female	144 (48.0%)
Year of Study	1st / 2nd / 3rd / 4th Year	72 / 69 / 72 / 87
Residential Status	Day Scholar / Hosteller	165 (55.0%) / 135 (45.0%)
Age	M = 22.62, SD = 3.59, range 17–28	

5.4 Research Instruments

Academic AI Usage Scale (AAIUS). Academic AI usage was measured using the AAIUS (Chakraborty & Subramani, 2025), a 24-item, five-point scale that produces a total score and three subscale scores: AI Dependence (9 items), Academic Support (11 items), and Academic Skills (4 items). The original validation study reported reliability of α = .856 for the total scale; reliability in the present illustrative sample was α = .841.

Psychological Well-Being Scale (PWBS-SDCP). Psychological well-being was measured using the PWBS-SDCP (Sisodia & Choudhary, 2012), a 50-item, five-point scale covering five areas of well-being (Satisfaction, Efficiency, Sociability, Mental Health, Interpersonal Relations), with a published reliability of .87. Reliability in the present illustrative sample was α = .839. Only the total score was analysed, as the official item-to-area scoring key is proprietary to the test publisher.

5.5 Procedure and Ethical Considerations

Students will complete both scales together with a short demographic questionnaire, after providing informed consent. Participation will be voluntary, responses will be anonymised, and institutional ethics approval will be obtained before data collection begins.

5.6 Statistical Technique

Data were analysed using Python (pandas, SciPy). Descriptive statistics and reliability (Cronbach's alpha) were computed for both scales. Students were divided into high and low AI-usage groups using a median split, and an independent-samples t-test compared the two groups on well-being, with Cohen's d reported as the effect size. Pearson correlations examined the relationship between well-being and (a) overall AI usage and (b) each of the three AAIUS subscales.

6. Results

Table 2

Reliability and Descriptive Statistics

Variable	Items	α	M	SD
AAIUS Total	24	.841	80.52	9.42
AI Dependence	9	.869	29.39	5.55
Academic Support	11	.860	37.67	5.86
Academic Skills	4	.620	13.46	2.26
PWBS-SDCP Total	50	.839	178.91	13.69

6.1 High vs. Low AI Users

Students were split into high (n = 154) and low (n = 146) AI-usage groups based on the median AAIUS total score (Mdn = 81.0). High AI users reported significantly higher

psychological well-being (M = 181.86, SD = 12.77) than low AI users (M = 175.79, SD = 13.98), t(292) = 3.92, p < .001, d = 0.45 — a small-to-medium effect (Cohen, 1988). The null hypothesis (H_0) is rejected, and H_1 is supported.

Table 3
Independent-Samples t-Test: Well-Being by AI-Usage Group

Group	n	M	SD	t	df	p	d
High AI Users	154	181.86	12.77	3.92	292	< .001	0.45
Low AI Users	146	175.79	13.98				

6.2 Does the Type of AI Use Matter?

Overall AI usage showed a small, significant positive correlation with well-being, r(298) = .221, p < .001. Looking at the three subscales separately gave a more specific picture: Academic Support (r = .252, p < .001) and Academic Skills (r = .254, p < .001) were both significantly related to higher well-being, while AI Dependence was not related to well-being at all (r = .006, p = .923). In other words, the overall benefit of AI use appears to come from using it to support learning and build skills — not from how much a student relies on it.

Table 4
Correlations Between AI-Usage Variables and Well-Being

AI-Usage Variable	r with Well-Being	p
AAIUS Total	.221	< .001
AI Dependence	.006	.923
Academic Support	.252	< .001
Academic Skills	.254	< .001

7. Discussion

The results show that students who use AI more overall report somewhat higher psychological well-being — but this is only part of the picture. The more useful finding is that this benefit comes specifically from using AI for academic support and skill-building, not from AI dependence. This fits with Self-Determination Theory (Ryan & Deci, 2000): AI use that helps students understand material and build their own abilities supports their sense of competence, while relying on AI without engaging with it does not offer the same benefit. It also matches recent findings that over-reliance on AI is linked to weaker independent thinking rather than better outcomes (Zhai et al., 2024; Zhang et al., 2024).

These findings should be read with two cautions in mind. First, because the design is correlational, it cannot show that AI use causes better well-being — students who are already doing well may simply be more likely to use AI in constructive ways. Second, as noted earlier, the specific numbers reported here come from a calibrated illustrative dataset and should be treated as a preview of the planned study rather than confirmed results.

8. Educational and Psychological Implications

- AI literacy programmes should teach students the difference between using AI to support learning and simply depending on it for answers.
- Assignments can be designed to make students' use of AI visible (e.g., through drafts or short reflections), encouraging supportive rather than dependent use.
- Faculty can combine AI-assisted learning with discussion and independent problem-solving to keep students actively engaged.
- Student counselling services can include AI use as part of broader conversations about healthy technology habits.

9. Limitations of the Study

- As explained in Section 5.2, the results reported here come from a calibrated illustrative dataset, not completed data collection, and should not yet be treated as confirmed findings.
- The design is cross-sectional and correlational, so causal claims cannot be made.
- Both AI use and well-being were measured through self-report, which may be affected by response bias.
- Only the total PWBS-SDCP score could be analysed, since the scale's official item-to-dimension key is proprietary.
- The sample will be drawn using purposive rather than random sampling, which may limit generalisability.

10. Suggestions for Future Research

- Complete data collection across the eight participating institutions and re-run this analysis on the real dataset.
- Use longitudinal designs to see whether changes in AI use over time relate to changes in well-being.
- Examine the five PWBS-SDCP dimensions separately, once the official scoring key is available.
- Explore other factors, such as academic discipline or digital literacy, that might influence whether students use AI supportively or dependently.

11. Conclusion

This study set out to examine how AI use relates to psychological well-being among university students, using two validated instruments and a more detailed look at different types of AI use. The illustrative analysis suggests that AI use is related to well-being, but not uniformly: students who use AI to support learning and build skills appear to benefit, while

simply depending on AI does not show the same benefit. If confirmed with real data, this suggests that the more useful question for educators is not whether students use AI, but how — and that AI-literacy efforts should be built around that distinction.

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