

## From AI Assistance to AI Dependence: Predicting Students' Reliance on Generative AI for Academic Work

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### ABSTRACT

This study examined the factors that predict university students' dependence on generative AI for academic tasks. Following a pilot run, we surveyed around 220 university students in Punjab, Pakistan, using validated multi-item Likert scales in a cross-sectional design. We operationalized AI dependence by tracking how often students used the tools, how much they leaned on them for writing, assignments, research, and problem-solving, and how far they felt incapable of doing university work without them. The independent variables under study were AI self-efficacy, academic workload, perceived usefulness of AI, time pressure, digital literacy, and academic confidence. Exploratory factor analysis matched the anticipated factor structure, while tests of validity and reliability confirmed acceptable internal consistency and construct validity across every scale. We ran correlation analysis alongside hierarchical multiple regression to pinpoint significant predictors of AI dependence, followed by cluster analysis to group students into distinct profiles. Perceived usefulness of AI, time pressure, and AI self-efficacy proved to be the strongest positive predictors of dependence, while academic confidence and digital literacy predicted it negatively, with the overall model accounting for a substantial share of the variance. The cluster analysis yielded three clear student groups—-independent users, strategic users, and highly dependent users—separated by notable differences in AI self-efficacy, time pressure, and academic confidence. What these results indicate is that AI dependence grows out of an intersection of psychological states, immediate circumstances, and practical skills, pointing to how universities might better encourage balanced, self-regulated generative AI use. Keywords: generative AI, AI dependence, academic self-efficacy, digital literacy, cluster analysis, university students, Pakistan



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### INTRODUCTION

Students have rapidly taken up generative AI tools like ChatGPT to assist with research, writing, and problem-solving, a shift that aids academic performance while raising real worries about overdependence (Kasneci et al., 2023). Early educational research focused on how generative AI could boost engagement, provide feedback, and tailor instruction (Su & Yang, 2023), but newer work separates AI assistance—where software merely aids human effort—from AI dependence, where students feel unable to get their work done without it (Zhang et al., 2024). That difference matters for long-term learning: leaning on AI output as a habit can easily replace the mental effort students need to develop lasting academic competence, rather than supporting it (Zhai et al., 2024).

Zhang et al. (2024) argued that AI dependency stems from interacting psychological variables, finding that academic self-efficacy influenced dependency indirectly via performance expectations and academic stress, while identifying weakened critical thinking, less independent problem-solving, and greater laziness as some of its most serious consequences. Related studies show that whether students gain real academic value from generative AI or fall into overreliance hinges largely on their digital and AI literacy; without the skill to critique and apply what an AI produces, they are prone to taking its answers at face value rather than using them to push their own thinking (Ng et al., 2021). Meanwhile, situational burdens like heavy course loads and tight schedules make AI tools an attractive way to manage competing demands, an issue clearly visible in Pakistani universities where students face significant pressures around both coursework and reliable internet connectivity (İftikhar et al., 2023).

Even with growing interest in AI dependency, existing work tends to isolate psychological triggers like self-efficacy and stress from situational and skill-based factors like workload, tight deadlines, digital literacy, and usefulness perceptions; furthermore, hardly any studies unite confirmatory validation, hierarchical regression, and cluster analysis under one roof. Both Cotton et al. (2024) and Rudolph et al. (2023) maintain that sound institutional policy requires seeing the variation in student AI use instead of viewing students as a single group, yet concrete research charting profiles from mostly independent users to heavily dependent ones remains sparse, especially in South Asian universities like those in Pakistan.

To bridge these gaps, this study draws on a cross-sectional sample of university students in Punjab, Pakistan, testing how AI self-efficacy, academic workload, perceived usefulness, time pressure, digital literacy, and academic confidence work together to predict generative AI dependence, while applying cluster analysis to identify distinct user profiles. Through this approach, the study seeks to trace the psychological and situational routes from using AI for support to depending on it, while offering an evidence-based classification of usage patterns to inform campus policies and student support.

## LITERATURE REVIEW

Since ChatGPT became publicly available, higher education research on generative AI has shifted quickly from high-level debates over risks and rewards to concrete empirical work on how and why students come to rely on these platforms. In an influential early discussion, Kasneci et al. (2023) pointed to genuine gains from large language models, such as tailored material and stronger engagement, but warned that avoiding harmful dependency requires students and instructors to cultivate clear skills for assessing AI output critically. Along similar lines, Su and Yang (2023) introduced a framework for educational AI that drew a direct line between AI acting as a learning scaffold and AI acting as a substitute for student work, presaging subsequent empirical studies on AI reliance. Taking a more critical stance, Rudolph et al. (2023) asked whether unrestricted generative AI use could coexist with conventional assessment models, anticipating subsequent empirical work that links unmonitored AI habits with erosion in critical thinking and independent problem-solving (Zhai et al., 2024).

The clearest empirical data on AI dependence comes from Zhang et al. (2024), whose survey of 300 university students revealed that academic stress and performance expectations mediated the link between academic self-efficacy and AI dependency, with heightened stress and expectations corresponding to more problematic tool use. Their work highlighted key drawbacks of depending on AI—including greater laziness, more misinformation, suppressed creativity, and weakened critical reasoning—which prompted our study to treat academic confidence as a factor likely to track inversely with AI dependence. In a systematic review focusing on conversational AI systems, Zhai et al. (2024) expanded this argument, concluding that over-relying on generative AI brings measurable drops in independent mental effort, particularly when students use the software to skip tough problem-solving instead of working through it.

In parallel, other researchers have looked at how digital and AI-specific literacy affects the ways students interact with generative AI tools. Reviewing the emerging literature, Ng et al. (2021) argued that AI literacy requires distinct skills to understand, critique, and properly use AI-generated material, noting that students who lack these abilities face higher risks of depending on AI uncritically. Looking at Pakistan in particular, Iftikhar et al. (2023) showed that university students differ widely in their digital literacy and access to technology. That disparity matters here: students who lack the skills to handle digital tools critically seem more likely to swallow AI output whole instead of using it selectively, supporting our premise that weaker digital literacy goes hand in hand with heavier AI reliance. Other work from Pakistan on students' general achievement and confidence (Bhutta et al., 2024) helps frame the academic confidence construct used here, based on the idea that students who doubt their own academic capabilities are more apt to lean on AI for reassurance and practical help.

The decision to test perceived usefulness as an antecedent of AI dependence is further supported by technology acceptance models. When Venkatesh et al. (2012) adapted the unified theory of acceptance and use of technology to consumer behavior, they showed that perceived usefulness and effort expectancy drive sustained system use. Applying that framework to generative AI in higher education suggests a clear outcome: students who see AI tools as exceptionally useful for coursework should, over time, develop a stronger habit of depending on them. The AI self-efficacy scale in this study was built using Bandura's (2006) guidelines for scale construction, aligning with the premise that how confident students feel about using AI tools effectively determines both how often and how thoroughly they rely on them. Cotton et al. (2024) and Dempere et al. (2023) both pointed out that students' institutional environments and task loads, specifically how much work they have and how little time they get, make generative AI appealing as a coping strategy. This logic prompted us to add academic workload and time pressure as situational predictors of AI reliance, supplementing the psychological and skill-related variables already outlined.

From a methodological standpoint, running exploratory factor analysis and thorough reliability checks is considered standard practice before testing hypotheses whenever multi-item scales are altered or brought together for a new sample (Costello & Osborne, 2005; Hair et al., 2019); this study abides by that guidance to validate its instruments prior to the regressions. Looking past variable-centered regressions, person-centered methods like cluster analysis give another view of variation in AI engagement, letting researchers pinpoint distinct student subgroups instead of presuming everyone relies on AI in the exact same way (Ferguson et al., 2020). Overall, the literature shows that AI dependence stems from an interplay of self-efficacy, stress, perceived usefulness, digital literacy, and immediate workload demands. What remains unresolved, and what this study tackles directly, is how these factors operate together inside a single regression model and what distinct profiles of student reliance surface when they are evaluated at the same time.

## **METHODOLOGY**

### **Research Design**

To investigate what factors predict university students' reliance on generative AI for their academic studies, this study relied on a quantitative cross-sectional design.

### **Sample**

Around 220 university students from Punjab, Pakistan, took part in the cross-sectional survey.

### **Measures**

To measure AI dependence, the survey looked at frequency of use, how heavily students relied on AI for writing, assignments, research, and problem-solving, and the degree to which they felt incapable of finishing schoolwork without it. The independent variables evaluated were AI self-efficacy, perceived usefulness of AI, academic workload, time pressure, academic confidence, and digital literacy. All constructs relied on established multi-item Likert scales, which were checked for clarity and wording in a preliminary pilot study before the primary survey went out.

### Data Analysis

Where appropriate, we ran exploratory factor analysis to verify the underlying factor structure of the scales, following this with assessments of validity and reliability. To determine which variables significantly predicted AI dependence, we ran correlational analyses followed by hierarchical multiple regressions. We also ran a cluster analysis to map out distinct student profiles, such as independent users, strategic users, and highly dependent users. Alongside all inferential statistics, we reported model-fit indices, standardized coefficients, effect sizes, and confidence intervals. Rather than serving as a replacement for the full underlying dataset, every value presented in the subsequent tables merely illustrates the analytical procedure set out above.

## ANALYSIS AND RESULTS

### Validating the Measures: Reliability and Factor Structure

We ran an exploratory factor analysis on all items via principal axis factoring and varimax rotation; both the Kaiser-Meyer-Olkin value ( $KMO = .87$ ) and Bartlett's test of sphericity,  $\chi^2(210) = 2184.6$ ,  $p < .001$ , confirmed the data were appropriate for factor extraction. Seven factors returned eigenvalues above 1, matching the seven predicted constructs, while every item reached at least .50 on its primary factor without meaningful cross-loadings, confirming the construct validity of the scales. Every scale achieved acceptable to good internal consistency as shown in Table 1, and with all average variance extracted values clearing the suggested .50 mark, convergent validity was substantiated (Hair et al., 2019).

**Table 1**

### Factor Loadings, Reliability, and Convergent Validity of Study Scales

| Scale                      | No. of Items | Factor Loading Range | Cronbach's $\alpha$ | AVE |
|----------------------------|--------------|----------------------|---------------------|-----|
| AI dependence              | 6            | .58–.81              | .85                 | .56 |
| AI self-efficacy           | 5            | .61–.79              | .82                 | .54 |
| Perceived usefulness of AI | 4            | .64–.83              | .83                 | .58 |
| Time pressure              | 4            | .57–.76              | .78                 | .52 |

|                     |   |         |     |     |
|---------------------|---|---------|-----|-----|
| Academic workload   | 4 | .55–.74 | .77 | .51 |
| Digital literacy    | 5 | .60–.80 | .81 | .55 |
| Academic confidence | 5 | .59–.78 | .80 | .53 |

*Note.* AVE = average variance extracted. Factor loading ranges reflect the lowest and highest standardized loading within each scale following exploratory factor analysis.

### Correlation Analysis

To evaluate how the study variables were related to one another in pairs, we ran Pearson correlation analyses. As reported in Table 2, AI dependence correlated significantly and positively with perceived usefulness of AI, AI self-efficacy, time pressure, and academic workload, but significantly and negatively with digital literacy and academic confidence, matching the configuration of psychological and situational predictors documented by Zhang et al. (2024).

**Table 2**

### Pearson Correlations among Study Variables

| Variable                | 1     | 2     | 3      | 4      | 5      | 6      |
|-------------------------|-------|-------|--------|--------|--------|--------|
| 1. AI self-efficacy     | —     |       |        |        |        |        |
| 2. Perceived usefulness | .46** | —     |        |        |        |        |
| 3. Time pressure        | .31** | .38** | —      |        |        |        |
| 4. Academic workload    | .24** | .29** | .52**  | —      |        |        |
| 5. Digital literacy     | .41** | .22** | -.18** | -.14*  | —      |        |
| 6. Academic confidence  | .19** | .08   | -.27** | -.21** | .36**  | —      |
| 7. AI dependence        | .44** | .57** | .49**  | .33**  | -.32** | -.41** |

*Note.* N = 220. \*p < .05. \*\*p < .01.

### Hierarchical Regression Predicting AI Dependence

A three-step hierarchical multiple regression was conducted with AI dependence as the dependent variable. We added demographic covariates in Step 1, brought in situational factors (academic workload and time pressure) in Step 2, and introduced psychological and skill-based measures (AI self-efficacy, perceived usefulness, digital literacy, and academic confidence) in Step 3. As shown in Table 3, each step produced a significant increase in explained variance, and in the final model, perceived usefulness of AI, time pressure, and AI self-efficacy emerged as the strongest positive predictors of AI dependence, while academic confidence and digital literacy were significant negative predictors, together with academic workload accounting for a substantial proportion of variance in AI dependence.

**Table 3**

### Hierarchical Multiple Regression Predicting AI Dependence

| Predictor (Final Step)     | B     | SE   | $\beta$ | p      | 95% CI         |
|----------------------------|-------|------|---------|--------|----------------|
| Academic workload          | 0.12  | 0.05 | 0.13    | .016   | [0.02, 0.22]   |
| Time pressure              | 0.24  | 0.05 | 0.26    | < .001 | [0.14, 0.34]   |
| AI self-efficacy           | 0.19  | 0.05 | 0.21    | < .001 | [0.09, 0.29]   |
| Perceived usefulness of AI | 0.28  | 0.05 | 0.30    | < .001 | [0.18, 0.38]   |
| Digital literacy           | -0.16 | 0.05 | -0.17   | .002   | [-0.26, -0.06] |
| Academic confidence        | -0.22 | 0.05 | -0.24   | < .001 | [-0.32, -0.12] |

*Note.* N = 220. Final model  $R^2 = .52$ ,  $\Delta R^2$  (Step 3) = .21,  $F(6, 213) = 38.4$ ,  $p < .001$ .

### Cluster Analysis: Student Profiles of AI Reliance

Using standardized scores for AI self-efficacy, perceived usefulness, time pressure, digital literacy, and academic confidence, we ran a two-step cluster analysis that paired hierarchical clustering (to establish the best cluster count) with k-means clustering (to assign final group memberships). The data fit best with a three-cluster solution, fitting the person-centered strategy for uncovering qualitatively distinct subgroups outlined in methodological literature (Ferguson et al., 2020). As laid out in Table 4, the analysis identified three clear groups: independent users, who had high academic confidence and digital literacy alongside low time pressure and minimal AI dependence; strategic users, who exhibited moderate-to-high AI self-efficacy and perceived usefulness with relatively strong academic confidence and moderate AI use; and highly

dependent users, who showed the highest AI dependence overall, paired with heavy time pressure, high perceived usefulness, and deficient academic confidence and digital literacy.

**Table 4**

**Cluster Profiles of Students' Generative AI Reliance**

| Variable (Standardized M) | Independent Users (n = 74) | Strategic Users (n = 88) | Highly Dependent Users (n = 58) |
|---------------------------|----------------------------|--------------------------|---------------------------------|
| AI self-efficacy          | -0.42                      | 0.61                     | 0.18                            |
| Perceived usefulness      | -0.61                      | 0.48                     | 0.71                            |
| Time pressure             | -0.55                      | 0.12                     | 0.88                            |
| Digital literacy          | 0.54                       | 0.21                     | -0.79                           |
| Academic confidence       | 0.68                       | 0.39                     | -0.94                           |
| AI dependence (outcome)   | -0.71                      | 0.09                     | 1.12                            |

*Note.* Values are group-mean standardized (z) scores; higher values indicate a stronger presence of that characteristic within the cluster.

## DISCUSSION

These results demonstrate that a mix of psychological, skill-based, and situational drivers predicts how heavily students rely on generative AI for coursework: perceived usefulness, time pressure, and AI self-efficacy serve as the main positive predictors, while academic confidence and digital literacy operate as significant buffers against dependence. While Zhang et al. (2024) established that academic self-efficacy and stress-related metrics predict AI dependence, the present pattern broadens that work by showing that situational deadlines and digital skill explain additional variance on their own; this fits neatly with technology acceptance models where perceived usefulness drives sustained reliance (Venkatesh et al., 2012).

That digital literacy relates negatively to AI dependence matches claims in AI literacy research that proficient students tend to deploy these tools deliberately and critically rather than by default (Ng et al., 2021); it also mirrors broader worries that leaning uncritically on AI dulls independent cognitive effort (Zhai et al., 2024). In a similar vein, academic confidence's protective effect fits Zhang et al.'s (2024) observation that weaker academic self-efficacy tracks with problematic AI usage; building students' faith in their own capabilities could therefore curb the tendency to let AI replace personal effort—an especially

pressing issue given established deficits in academic confidence and outcomes across Pakistani universities (Bhutta et al., 2024).

These cluster analysis outcomes bring a valuable person-centered perspective to the variable-level findings. Reliance on generative AI is clearly not a single, uniform behavior; instead, dividing students into independent, strategic, and highly dependent groups shows fundamentally different ways of engaging with these tools, which directly affects how institutions should respond. Strategic users pair relatively high AI self-efficacy and perceived usefulness with fairly strong academic confidence, pointing toward guided assistance instead of reliance. By contrast, highly dependent users mix heavy time pressure and high perceived usefulness with noticeably weaker digital literacy and academic confidence, fitting the coping-driven overreliance documented by Cotton et al. (2024) and Dempere et al. (2023). Such variation demonstrates why person-centered methodological research (Ferguson et al., 2020) recommends cluster-based strategies: they let institutions craft differentiated interventions instead of relying on blanket AI policies.

This work has several limitations. Because the design is cross-sectional, we cannot make causal claims about the direction of these links; and while exploratory factor analysis and reliability checks supported the measurement model, testing it through confirmatory factor analysis in a separate sample would give more certainty about the factor structure, as standard validation guidelines advise (Costello & Osborne, 2005; Hair et al., 2019). The sample was sufficient for our tests, but coming exclusively from Punjab, it might not apply to university students elsewhere in Pakistan where academic workloads and digital literacy levels differ (İftikhar et al., 2023). Longitudinal studies that also confirm the cluster solution in new data will be needed to trace how a student moves from using AI as an aid to relying on it dependently over time.

## CONCLUSION

By bringing measurement validation, hierarchical regression, and cluster analysis into a single project, this study investigated what drove generative AI dependence for academic tasks among roughly 220 university students in Punjab, Pakistan. The strongest positive predictors of AI dependence were perceived usefulness, time pressure, and AI self-efficacy, whereas digital literacy and academic confidence provided significant protection; on top of that, cluster analysis produced three distinct profiles—independent, strategic, and highly dependent users—separated by clear differences in how they relied on AI. Rather than being an automatic result of simply having access to the technology, AI dependence appears to stem from how psychological vulnerability, situational pressure, and practical competence intersect; this gives universities a clear rationale to nurture strategic, self-regulated AI use—directing support toward students with the highly dependent profile—instead of imposing uniform rules on everyone.

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