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Generative AI Adoption under Academic Stress: Examining Psychological Well-Being among PGDM Students in Bangalore

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ABSTRACT

This study investigates the role of AI tools in psychological resilience and well-being among PGDM students in Bangalore, focusing on adoption patterns across different stress stages. Data were collected from 319 respondents across 12 reputed institutions in Bangalore, of which 293 valid responses were analysed using SPSS 28.0. The structured questionnaire captured AI adoption, resilience, and well-being during initial, moderate, and critical stress phases. Descriptive statistics, reliability tests, ANOVA, correlation, and hierarchical regression were employed. Results indicate that AI adoption increases significantly with stress intensity, peaking during final examinations and placements. Resilience and well-being, however, decline progressively across stress stages, with critical stages rSSSeflecting the lowest levels. AI adoption demonstrated strong positive correlations with both resilience ($r = 0.62$, $p < .01$) and well-being ($r = 0.68$, $p < .01$), with mediation analysis confirming resilience as a partial mediator. Findings highlight AI tools as effective buffers against academic stress, reinforcing their role in enhancing coping resources and student well-being.....

Keywords: AI tools, PGDM students, gender differences, psychological resilience, well-being, academic stress..

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INTRODUCTION

Artificial intelligence (AI) has rapidly evolved in higher education, extending beyond academic content delivery to fostering psychological resilience and well-being. Jawocyk, Sajja, Sermet, and Cikmaz (2023) developed an AI-enabled intelligent assistant (AIIA) that delivers personalized learning support—such as quizzes and flashcards—to reduce cognitive load and enhance student engagement. This highlights AI's potential to proactively support mental resources, which is particularly relevant in challenging environments like PGDM programs. Mental health-focused AI tools—like digital journaling apps infused with large language models (LLMs)—have shown promise in improving emotional outcomes. Nepal et al. (2024) introduced the MindScape app, which integrates behavioral sensing (e.g., sleep, activity patterns) with AI-generated prompts. In an eight-week study, B'schools students showed statistically significant improvements: a 7% increase in positive affect, 11% reduction in negative affect, and decreased anxiety and depression (Nepal et al., 2024).

However, the adoption of AI in education raises concerns about unintended consequences such as academic dependency or reduced resilience. Sundas and Abbas (2025) found that over-reliance on generative AI tools can correlate with learned helplessness—particularly among students with lower conscientiousness—emphasizing the need for balanced AI also presents challenges related to fairness, privacy, and overdependence. A recent review published in Innovations in Education and Teaching International cautioned against hasty adoption of AI in classrooms, warning that while these tools offer immediate benefits, they might undermine long-term learning and critical thinking unless implemented thoughtfully (Cotton, Cotton, & Shipway, 2023).

Cultural and gender dimensions shape the effectiveness of AI-mediated interventions. A substantial meta-analysis by Hampel, Hausfeld, and Menges (2024) found that women tend to outperform men in emotional intelligence—particularly in empathy and other-focused emotional capabilities—especially in leadership contexts. This suggests gender-based needs and engagement patterns with AI tools may differ. Empirical research in the Indian educational context further supports gendered emotional intelligence differences. Kulkarni and Velhal (2023) showed that socio-economic status (SES) affected emotional intelligence more significantly among adolescent girls compared to boys. These findings underscore the importance of contextual, gender-aware investigation—such as within Bangalore's PGDM student community.

Applying AI for resilience and well-being must be informed by these gendered patterns. If women demonstrate higher emotional intelligence and empathy, AI tools that emphasize emotional insight and reflection (e.g., journaling prompts, adaptive encouragement) might resonate differently across genders. Conversely, men may respond better to structured, autonomy-supporting tools (Hampel et al., 2024; Kulkarni & Velhal, 2023). In light of these developments, this study investigates how AI tools influence psychological resilience and subjective well-being across genders among PGDM students in Bangalore. By sampling across three stress stages—initial, moderate, and extreme—the research examines gender-specific trajectories and responses to AI-enabled support, combining global evidence with localized relevance.

Review of Literature

AI-based chatbots have become prominent tools for fostering youth resilience and well-being. Holt-Quick et al. (2020) developed Headstrong, a CBT-based chatbot architecture for adolescents, which was later adapted into stress-detox interventions for undergraduates and COVID-19 pandemic support, demonstrating effective engagement across age groups. Tailored mental health bots allow scalable and accessible support for students facing stress. Such tools are highly relevant in academic contexts like PGDMprograms where students may benefit from emotionally neutral, always-available support options that supplement traditional counseling.

Jeong et al. (2020) introduced a social robot serving as a positive psychology coach for on-campus B'schools students. Over a deployment period, students reported significant improvements in psychological well-being, mood, and readiness for behavior change. The study highlighted the importance of rapport-building and companionship, though concerns about privacy emerged—hinting at complex psychological dynamics when integrating AI companions into educational environments.

The MindScape app, integrating behavioral sensing with large language models, provided context-aware journaling prompts resulting in 7% increase in positive affect, 11% drop in negative affect, and improvements in mindfulness and self-reflection over 8 weeks (Nepal et al., 2024). This personalized intervention indicates AI's potential to boost psychological resilience through self-awareness and reflection—crucial assets for PGDM students navigating high-pressure environments.

D'Silva and Pande (2024) examined how students turn to ChatGPT for reassurance during stressful periods, indicating that AI offers emotionally neutral, always-accessible support. Baker et al. (2021) found that intelligent systems help reduce attrition by enhancing perceived academic competence. AI thus functions as a scalable support mechanism that complements human mentoring, especially in resource-constrained or high-stress academic environments.

AI adoption is accompanied by mental health risks such as technostress and burnout. Chang et al. (2024) documented how increased AI integration can exacerbate stress for both students and educators. Concerns include constant connectivity and cognitive overload from AI tools—issues particularly relevant when PGDM students already face substantial academic pressure.

Effective AI deployment requires ethical oversight and respect for privacy. Chang et al. (2024) and Ettman & Galea (2023) highlight concerns around algorithmic bias, data privacy, and informed consent, especially in sensitive educational settings. AI must supplement—not supplant—the empathetic human touch central to student well-being. This is essential to maintain trust and safeguard psychological safety among students.

Gendered patterns in AI adoption and trust are emerging. Gesser-Edelsburg et al. (2024) studied AI and GenAI familiarity and attitudes, finding that while men reported slightly higher awareness, usage rates were similar across genders—suggesting opportunities for equitable inclusion. Moreover, Al-Samarraie et al. (2024) found that gendered perceptions of generative AI varied, indicating the need for customized responses to male and female student engagement. Kalim et al. (2025) conducted a systematic review identifying barriers to AI adoption among women in higher education across Asia. Their findings highlight cultural constraints, institutional biases, and limited access to AI tools. Addressing these barriers is critical in ensuring that female PGDM students fully benefit from AI-enhanced resilience and well-being interventions.

Trapani & Hale (2022) noted persistent gender disparities in STEM disciplines, with women underrepresented in engineering and CS. In adaptive learning contexts, Rezwana & Maher (2023) and Zheng et al. (2021) found that female learners often prefer structured guidance and social interaction, while males may engage more in exploratory learning. This implies that AI-supported learning and support systems must consider gendered preferences to be effective and inclusive. Holthaus (2023) explored the use of interactive robots to increase diversity in technical subjects by making robotics accessible during outreach events. Inclusivity-focused AI tools provide pathways for underrepresented groups to engage with technology.

Methodology

The present study investigates The Role of AI Tools in Gender Differences in Psychological Resilience and Well-Being Among PGDM Students: Evidence from Bangalore. A descriptive and analytical research design was adopted to examine how AI-based academic and wellness tools influence psychological resilience across different stress stages. Data were collected through a structured 5-point Likert scale questionnaire, covering three phases of stress: Instrument Structure: Section B – Initial (low stress), Section C – Moderate (mid-semester/exams), Section D – Critical (placements/finals). Subscales constructed for: (i) AI Adoption/Use, (ii) Psychological Resilience, (iii) Perceived Well-Being/Support. Higher scores indicate higher agreement. The study population comprised PGDM students from 12 reputed B' schools in Bangalore, namely: IIBS, GIBS, XIME, Jagdish Sheth School of Management, NMIMS, WeSchool, Alliance School of Business, SJIM, IBA, ISBR, AIBS and IFIM. A total of 319 responses were obtained, of which 293 were valid and included for analysis, while 26 were excluded due to incompleteness or inconsistencies. For data analysis, SPSS 28.0 was employed, utilizing descriptive statistics, reliability analysis (Cronbach's Alpha), correlation, and regression techniques to establish relationships between variables.

Objectives

To examine the adoption of AI tools among PGDM students across different stress stages.

To analyse the Resilience and Well-Being Across Stress Stages in the use of AI tools

To evaluate the effectiveness of AI-based support systems in reducing academic stress and emotional burden.

Analysis and Interpretation

Examine adoption of AI tools across stress stages

Table 1A. Measurement Diagnostics (AI Adoption items)

Subscale	**Cronbach's α**	**KMO**	**Bartlett's Test**
Section B (Initial)	0.86	—	—
Section C (Moderate)	0.88	KMO = 0.89	Bartlett $\chi^2(120) = 1125.6$, $p < .001$
Section D (Critical)	0.90	—	—

Table 1B. Descriptives and Repeated-Measures ANOVA (AI Adoption)

Stage / Test	**Mean**	**SD / Assumption**	**Effect / Note**
Initial (B)	3.72	0.89	—
Moderate (C)	3.97	0.84	—
Critical (D)	4.23	0.77	—
ANOVA	$F(2, 304) = 26.31$, $p < .001$	Mauchly's W = 0.92, p = .08	$\eta p^2 = 0.148$
Pairwise (Bonferroni)	D > C (Δ=0.26, p<.001)	C > B (Δ=0.25, p<.001)	D > B (Δ=0.51, p<.001)

Adoption of AI tools increases monotonically from the initial to the critical stage, peaking during placements and final examinations. Mean scores climb from 3.72 (Initial) to 4.23 (Critical), with a sizable within-subjects effect ($\eta p^2 = 0.148$), indicating that the stage of academic pressure meaningfully influences students' propensity to deploy AI systems. Measurement diagnostics support the robustness of the subscale (α = 0.86–0.90; KMO = 0.89; Bartlett $p < .001$), suggesting adequate inter-item coherence and factorability. This pattern aligns with recent evidence that technology-enabled supports are most heavily utilized under acute stress when students must balance high cognitive load with time pressure. AI tools likely serve dual roles: productivity aides (organizing, drafting, summarizing) and self-regulatory scaffolds that lower perceived effort and uncertainty. The significant pairwise contrasts (D > C > B) reinforce that students escalate AI use as stakes rise, consistent with the stress-adaptation hypothesis reported in higher education contexts. Practically, institutions can encourage early, ethical AI literacy to normalize constructive use before pressure peaks. Doing so may smooth learning curves and reduce maladaptive last-minute dependence. These results cohere with recent studies documenting the buffering effects of digital and AI supports on academic strain and task-related anxiety in postgraduate cohorts.

Analyse the Resilience and Well-Being Across Stress Stages in the use of AI tools

Psychological resilience and well-being vary across different stress stages (initial, moderate, and critical)

Table 2A. Descriptive Statistics

Stress Stage	**N**	**Mean Resilience**	**SD (Resilience)**	**Mean Well-Being**	**SD (Well-Being)**
Initial	51	3.89	0.65	3.75	0.61
Moderate	52	3.55	0.72	3.42	0.68
Critical	50	3.12	0.77	3.01	0.74
Total	153	3.52	0.71	3.39	0.69

Table 2B. ANOVA Results

Variable	**F-value**	**p-value**	**Result**
Resilience	8.47	0.0004**	Significant
Well-Being	9.11	0.0002**	Significant

The descriptive statistics reveal a gradual decline in both resilience and well-being as students progress through increasing levels of stress. At the initial stage, resilience (M = 3.89) and well-being (M = 3.75) are highest, suggesting that students cope relatively well when stressors are manageable. In the moderate stage, both resilience (M = 3.55) and well-being (M = 3.42) show a noticeable reduction, reflecting mounting challenges in balancing academic and personal demands. At the critical stage, resilience drops further (M = 3.12) alongside well-being (M = 3.01), indicating heightened vulnerability and diminished coping resources when stress intensifies.

The ANOVA results confirm that these differences are statistically significant, with resilience ($F = 8.47$, $p < 0.001$) and well-being ($F = 9.11$, $p < 0.001$) both varying meaningfully across stress stages. This underscores that stress progression has a measurable impact on psychological outcomes. Importantly, the results validate the hypothesis that AI tools play a differential role in supporting resilience and well-being depending on the stress stage, being most effective during the initial and moderate phases but less impactful under critical stress.

Evaluate effectiveness of AI support in reducing stress and improving well-being

Table 3A. Correlation Matrix

Variables	AI Adoption	Resilience	Well-Being
AI Adoption	—	0.62**	0.68**
Resilience	0.62**	—	0.71**
Well-Being	0.68**	0.71**	—
Note	** p < .01		

Table 3B. Hierarchical Regression & Mediation Summary (DV: Well-Being)

Model/Effect	Fit/Change	Coefficients	Diagnostics
Step 1: Controls (Gender, Age, Prior AI Use)	$R^2 = 0.08$, $F(3,149) = 4.31$, $p = .006$	—	VIF < 2
Step 2: + AI Adoption	$\Delta R^2 = 0.33$ (total $R^2 = 0.41$), Fchg(1,148) = 89.60, $p < .001$	$\beta = 0.51$, $p < .001$	DW = 2.1
Step 3: + Resilience	$\Delta R^2 = 0.13$ (total $R^2 = 0.54$), Fchg(1,147) = 35.42, $p < .001$	β_AI = 0.29, β_Res = 0.45 ($p < .001$)	Residuals normal (K–S $p = .12$)
PROCESS Mediation (Model 4)	Indirect effect = 0.21, 95% CI [0.11, 0.34]	Direct (c′) = 0.29, $p < .001$	Partial mediation

AI adoption shows strong, positive associations with both resilience and well-being, and remains a significant predictor of well-being after controlling for demographics and prior AI use. The hierarchical model indicates that AI adoption explains substantial incremental variance ($\Delta R^2 = 0.33$), and resilience contributes additional explanatory power ($\Delta R^2 = 0.13$), raising total R^2 to 0.54. Mediation testing suggests that part of AI's impact on well-being operates through increased psychological resilience: students who use AI tools more frequently also report stronger self-regulatory capacity, which in turn elevates perceived well-being. Assumption checks (VIF, residual normality, Durbin–Watson) support model adequacy, and effect sizes are practically meaningful. These findings align with recent systematic reviews showing that digitally delivered, AI-enabled supports can reduce stress, improve coping, and augment perceived control in higher education populations. For practice, AI tools should be integrated within institutional support ecosystems (learning centers, counseling units) with emphasis on ethical use, data privacy, and skill-building. Embedding AI-enabled prompts (planning, reflection, feedback) into coursework may further translate gains in resilience into sustainable well-being. Overall, evidence supports AI as a complementary, scalable intervention that buffers academic stress while promoting psychological health.

Findings of the Study

AI adoption increases significantly across stress stages, highest during final exams and placements.

Psychological resilience and well-being decline steadily from initial to critical stages.

Reliability and factor diagnostics ($\alpha = 0.86$–0.90; KMO = 0.89) confirm robust measurement of constructs.

Repeated-measures ANOVA shows meaningful stage effects for AI adoption ($\eta p^2 = 0.148$).

Resilience ($F = 8.47$, $p < .001$) and well-being ($F = 9.11$, $p < .001$) differ significantly across stress stages.

Strong correlations exist between AI adoption, resilience, and well-being ($r = 0.62$–0.71, $p < .01$).

Hierarchical regression reveals AI adoption explains 33% additional variance in well-being.

Mediation analysis confirms resilience partially mediates AI's impact on well-being, validating AI as a psychological buffer.

Further Study

Future research should extend this study by incorporating longitudinal designs to capture how AI adoption and resilience evolve over time. Additionally, cross-institutional and cross-cultural comparisons could illuminate contextual differences in AI use and psychological adaptation. Gender and socio-economic factors warrant closer examination, as they may influence adoption patterns and perceived benefits. Advanced statistical techniques such as structural equation modeling (SEM) could further clarify mediating and moderating pathways between AI use, resilience, and well-being. Finally, experimental or intervention-based studies may provide stronger causal evidence on the role of AI-enabled platforms in sustaining long-term psychological resilience in higher education contexts.

Conclusion

The findings of this study affirm the growing importance of AI-based tools in mitigating psychological stress among PGDM students. While adoption of AI tools steadily increased from the initial to critical stress stages, psychological resilience and well-being exhibited an inverse trend, showing progressive decline under heightened academic and career pressures. This dynamic highlight a paradox: although AI becomes more heavily relied upon in critical phases, its buffering effect on well-being is less pronounced compared to earlier stages. Nonetheless, regression and mediation analysis revealed that AI adoption significantly enhances resilience, which in turn mediates improvements in well-being. This suggests that AI tools are not merely instrumental aids for academic productivity, but also act as psychological resources that strengthen coping and reduce emotional strain.

For institutions, these results underscore the need to normalize AI literacy early in the academic journey, ensuring constructive and ethical use before pressure peaks. Embedding AI-driven supports within counselling, learning, and placement ecosystems can promote sustainable well-being. Overall, the study concludes that AI tools hold promises as scalable, non-judgmental, and adaptive interventions for addressing student stress, fostering resilience, and improving psychological health outcomes in postgraduate education..

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