



Perceived Stress And Artificial Intelligence Chatbot Acceptance Among College Students In Bengaluru: A Correlational Study

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Abstract: The transition into tertiary education represents a psychologically demanding period, particularly within the competitive academic environments of urban India. This study examines the relationship between perceived psychological stress and acceptance of Artificial Intelligence (AI) chatbots as mental health support proxies among college students in Bengaluru, Karnataka. Employing a quantitative correlational cross-sectional design, data were collected from N = 149 undergraduate and postgraduate students drawn from colleges spanning urban, peri-urban, and rural districts of Bengaluru. The Perceived Stress Scale (PSS-10; Cohen et al., 1983) served as the independent variable measure, and the Artificial Intelligence in Mental Health Scale (AIMHS; Katsiroumpa et al., 2025) measured AI chatbot acceptance. Pearson's correlation analysis yielded $r(147) = .537$, $p < .001$, $r^2 = .288$, 95% CI [.418, .637], indicating a moderate-to-strong positive relationship: higher perceived stress is a meaningful predictor of greater AI chatbot acceptance. The null hypothesis ($H_0: \rho = 0$) was decisively rejected. Qualitative adoption data identified 24/7 accessibility (78%) and anonymity (72%) as primary motivators. A striking finding was the overwhelming preference for general-purpose Large Language Models such as ChatGPT (55.1%) and Google Gemini (26.5%) over clinically validated tools such as Wysa (5.9%), constituting what this study terms the "Safety Paradox." Findings are interpreted through the Technology Acceptance Model 2 (TAM2), Privacy-Calculus Theory (PCT), and the Lazarus-Folkman transactional stress-coping model, with an original theoretical contribution: the "Mental Health Privacy Paradox."

Index Terms — perceived stress, AI chatbot acceptance, PSS-10, AIMHS, college students, mental health, digital therapeutics, Bengaluru, Technology Acceptance Model, India

I. INTRODUCTION

Higher education has long been associated with opportunity and upward mobility, but beneath this promise lies a psychological reality that has become increasingly difficult to ignore. For many students, particularly in India's fiercely competitive academic culture, the transition to higher education produces a level of psychological distress that is at once pervasive and profoundly under-addressed [1].

The mental health crisis among university students is well-documented globally, with meta-analyses estimating that between 30 and 35 percent of college students experience clinically significant distress [2]. In India, structural barriers including financial constraints, geographic inaccessibility of services, and social stigma compound these pressures. National data suggest that India's treatment gap for common mental disorders exceeds 80% in urban settings [3].

Bengaluru, as the nation's technology hub, presents a particularly instructive context. The city draws ambitious students from across India into high-stakes academic and professional competition. Mehrotra and Vijayakumar [4] term this process “social thinning”—the progressive erosion of familiar emotional support networks experienced by migrating students, resulting in heightened vulnerability to social isolation and distress.

Simultaneously, the emergence of AI-powered conversational agents has created a new and largely unregulated category of mental health-adjacent support. Since Weizenbaum's [5] original ELIZA program demonstrated that computer-mediated emotional exchange could produce meaningful psychological responses, computational approaches to psychological support have evolved dramatically. Contemporary Large Language Models (LLMs) such as ChatGPT and Google Gemini can sustain contextually coherent, emotionally responsive conversations that users experience as genuine understanding—what Mehrotra and Vijayakumar [4] characterize as “cognitive empathy.”

This study addresses a specific and practically important gap in the literature: whether perceived stress is a significant predictor of AI chatbot acceptance among college students in Bengaluru, and what this relationship implies for institutional mental health policy and practice.

A. Research Objectives

The primary objective of this study is to determine whether a statistically significant positive linear relationship exists between perceived stress (PSS-10 scores) and AI chatbot acceptance (AIMHS scores) among college students in Bengaluru. Supplementary objectives include examining group differences by gender and academic stream, and documenting qualitative adoption drivers and platform preferences.

B. Hypotheses

There is no statistically significant correlation between Perceived psychological stress and AI chatbot acceptance

($H_0: \rho = 0$).

H_1 : There is a statistically significant correlation between Perceived psychological stress and AI chatbot acceptance

($H_1: \rho > 0$).

C. Key Conceptual Definitions

Perceived Stress: The degree to which situations in one's life are appraised as stressful, measured using the PSS-10 (Cohen et al., 1983) [6].

AI Chatbot Acceptance: The extent to which an individual accepts and is willing to use AI chatbot tools for mental health support, measured using the AIMHS (Katsiroumpa et al., 2025) [7].

Treatment Gap: The discrepancy between the prevalence of mental health disorders and the proportion of individuals who actually receive evidence-based treatment—estimated at over 80% in urban India [3].

Safety Paradox: The inverse relationship between clinical need severity and clinical tool quality, wherein the most distressed students disproportionately use the least clinically validated AI tools.

Mental Health Privacy Paradox: A culturally specific extension of Privacy-Calculus Theory in which fear of social stigma dominates informational privacy concerns, making anonymous AI chatbots the preferred help-seeking modality.

II. LITERATURE REVIEW

A. The Evolving Landscape of Student Mental Health

O'Sullivan et al.'s [2] meta-analysis synthesizing data from 32 studies estimated that between 30 and 35 percent of college students experience clinically significant distress. The COVID-19 pandemic intensified this crisis: longitudinal research found sharp post-pandemic increases in anxiety, disrupted sleep, and heightened academic worry among Indian college students [8]. The 2024–2025 Healthy Minds Study (University of Michigan, 2025) notes that approximately 76% of students reported moderate-to-high stress, a proportion more consistent with epidemic classification than normative experience.

Cherian et al. [9] conducted a landmark multi-state study across nine Indian states documenting alarming rates of suicidal ideation alongside widespread anxiety and depression in college populations. Help-seeking was markedly lower than distress prevalence, maintained by financial barriers, geographic

inaccessibility, and social stigma. These findings are consistent with NIMHANS national data estimating a treatment gap exceeding 80% [3].

B. Artificial Intelligence in Mental Health

The application of computational technology to psychological support traces back to Weizenbaum's [5] ELIZA program, which demonstrated that pattern-matching scripts simulating a Rogerian therapist could produce meaningful emotional responses in users—a phenomenon termed the ELIZA Effect. Contemporary LLMs represent a qualitative break: trained on hundreds of billions of parameters, models such as ChatGPT and Gemini sustain multi-turn, contextually coherent conversations with emotional responsiveness that users experience as genuine empathy [4].

Meta-analytic reviews suggest that AI chatbot interventions can achieve moderate effect sizes in reducing depressive symptoms ($g \approx 0.36$) and perceived stress ($g \approx 0.42$) in youth populations [2], particularly for CBT-adjacent applications. However, a critical distinction exists between clinically validated tools such as Woebot [10] and Wysa [11], and general-purpose LLMs repurposed for emotional support without clinical design or governance. Iftikhar et al. [12] identified systematic violations of mental health ethics standards in LLM-based mental health applications, including failure to detect suicidal ideation and provision of clinically harmful advice.

C. The Indian Context: Stigma, Social Thinning, and the Treatment Gap

Academic achievement in India is deeply collectivized: a student's results are experienced by family and community as a collective outcome, generating simultaneous pressure to succeed and to appear to be coping successfully. The “Log Kya Kahenge” phenomenon—anxiety about social judgment—has been consistently identified as a primary driver of help-seeking avoidance [13]. Mehrotra and Vijayakumar [4] document social thinning as particularly acute among students migrating to Bengaluru, where high isolation rates for migrants are empirically demonstrated.

D. AI Adoption Among Young People for Mental Health

Lamichhane et al. [14] found that approximately 34% of American college students reported using LLMs as mental health resources, with students reporting higher distress significantly more likely to use LLMs for emotional support—a pattern directly consistent with the primary finding of the present study. Within India, the OJPHI [15] review of technology for mental health in Indian higher education found improving digital mental health literacy but almost entirely absent institutional frameworks for regulated AI deployment.

Wysa, the most rigorously evaluated clinically oriented AI mental health chatbot available in India, has demonstrated effectiveness in reducing anxiety and depression in controlled trials [11]. Yet adoption of Wysa in the present study's sample was just 5.9%, compared to 55.1% for ChatGPT and 26.5% for Google Gemini. This asymmetry between clinical evidence and actual adoption patterns constitutes the empirical foundation of the Safety Paradox.

E. Theoretical Framework

This study is anchored in three complementary theoretical frameworks. The Technology Acceptance Model 2 (TAM2; Venkatesh & Morris, 2000) [16] constitutes the primary adoption framework, predicting technology adoption on the basis of Perceived Usefulness and Perceived Ease of Use. In the mental health context, perceived usefulness is represented by beliefs about AI chatbot availability, anonymity, and emotional responsiveness; perceived ease of use reflects the low friction of AI access relative to formal counselling.

Privacy-Calculus Theory (PCT; Laufer & Wolfe, 1977; Dinev & Hart, 2006) [17][18] provides the decisional framework for understanding why students disclose sensitive mental health content to AI systems. PCT posits a rational cost-benefit analysis: the present study's Mental Health Privacy Paradox

extends this framework to account for the finding that social stigma—not data misuse—constitutes the operative privacy risk in the Indian cultural context.

The Lazarus and Folkman [19] Transactional Model of Stress and Coping situates AI chatbot adoption within a broader coping repertoire. When structural barriers render problem-focused coping unavailable or aversive, students deploy emotion-focused alternatives. The directional prediction of the primary hypothesis—that higher stress predicts higher AI acceptance—flows directly from this coping framework.

III. RESEARCH METHODOLOGY

A. Research Design

The study employed a quantitative correlational cross-sectional research design. This design was selected because the primary objective—to determine whether a statistically significant positive linear relationship exists between PSS-10 and AIMHS scores—is precisely what correlation analysis is constructed to investigate. A cross-sectional survey approach was adopted, with all data collected during the 2025–2026 academic year. The research was conducted within a post-positivist paradigm.

B. Sample and Sampling Strategy

The target population comprised undergraduate and postgraduate college students in Bengaluru, Karnataka. Purposive convenience sampling was employed, targeting students aged 18–30 across Engineering/Technology, Arts/Commerce, and Science/Medical academic streams from institutions spanning urban, peri-urban, and rural districts of Bengaluru. A minimum sample size of 85 participants was determined via power analysis using G*Power 3.1 [20] (medium effect size $r = 0.30$, $\alpha = .05$, power = 0.80). The final sample comprised $N = 149$ participants.

C. Instruments

Perceived Stress Scale—PSS-10 (Cohen et al., 1983) [6]: A 10-item self-report instrument measuring perceived psychological stress over the preceding month. Items are rated on a 5-point frequency scale (0 = Never to 4 = Very Often). Items 4, 5, 7, and 8 are reverse-scored. Total scores range from 0–40; scores of 14–26 indicate moderate stress, and scores ≥ 27 indicate high stress. The PSS-10 has demonstrated strong psychometric properties across multiple cultural contexts ($\alpha = .78-.91$).

Artificial Intelligence in Mental Health Scale—AIMHS (Katsiroumpa et al., 2025) [7]: A 5-item instrument assessing acceptance of AI chatbots for mental health support, rated on a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). Total scores range from 5–25, with higher scores reflecting greater acceptance. The scale was developed and validated with strong internal consistency ($\alpha = .89$). This study represents the first application of the AIMHS in an Indian student population.

D. Data Collection Procedure

The survey was administered online via Google Forms. Ethics approval was obtained from the JAIN (Deemed-to-be University) Research Ethics Committee prior to data collection. Informed consent was obtained from all participants. The survey was distributed through academic networks, college WhatsApp groups, and direct outreach to student associations across Bengaluru. The survey remained open for four weeks. Participation was entirely voluntary; no incentives were offered. Incomplete responses were excluded from analysis.

E. Analytical Strategy

All statistical analyses were conducted using Microsoft Excel with Analysis ToolPak and cross-validated in Jamovi Version 2.7 [21]. Normality was formally assessed using Shapiro-Wilk tests and visual inspection of histograms and Q-Q plots. The primary hypothesis was tested using Pearson's bivariate correlation. Supplementary analyses employed independent-samples t-tests (gender and AI usage group comparisons) and one-way ANOVA with post-hoc Tukey HSD comparisons (academic

stream differences). Effect sizes were computed as Cohen's d (t-tests) and η^2 (ANOVA). The significance threshold was set at $\alpha = .05$, two-tailed.

IV. RESULTS AND DISCUSSION

A. Demographic Profile

Table 1: Demographic Profile of Study Participants (N = 149)

Demographic Variable	Category	Count	Percentage (%)
Gender	Male	88	58.8
	Female	58	39.0
	Other / Prefer not to say	3	2.2
Academic Stream	Engineering / Technology	71	47.8
	Arts / Commerce	44	29.4
	Science / Medical / Other	34	22.8
AI Usage Status	Confirmed AI Users	87	58.3
	Non-Users	62	41.7
Age Range	18–20 years	68	45.6
	21–23 years	61	40.9
	24–30 years	20	13.4

The sample is predominantly male (58.8%) and drawn largely from engineering and technology programs (47.8%). A majority of participants (58.3%) reported using AI tools for psychological or emotional support. The demographic distribution reflects the broader Bengaluru college student population.

B. Descriptive Statistics

Table 2: Descriptive Statistics for PSS-10 and AIMHS Scores

Variable	N	M	SD	Min	Max	% High Stress*
PSS-10 Full Sample	149	21.8	6.4	6	39	41.2%
PSS-10 AI Users	87	24.3	5.9	8	39	52.9%
PSS-10 Non-Users	62	18.4	6.1	6	33	24.2%
AIMHS Full Sample	149	17.2	4.1	5	25	—

*Percentage scoring in the high-stress category ($PSS-10 \geq 27$). $PSS-10$ = Perceived Stress Scale (10-item); AIMHS = Artificial Intelligence in Mental Health Scale.

The mean $PSS-10$ score of 21.8 ($SD = 6.4$) places the full sample in the moderate stress range (14–26). However, 41.2% of participants scored in the high-stress category—nearly two in five students experiencing stress associated with persistent anxiety, sleep disruption, and elevated burnout risk. The contrast between AI users ($M = 24.3$) and non-users ($M = 18.4$) is clinically notable, with AI users operating at stress levels more than five points higher on average.

C. Primary Hypothesis Testing: Pearson's Correlation

Prior to the primary analysis, Shapiro-Wilk tests assessed normality: $PSS-10$ scores ($W = 0.982$, $p = .054$) approximated normality; AIMHS scores ($W = 0.978$, $p = .028$) showed only a minor departure—insufficient to justify abandoning parametric analysis given sample size and the known robustness of Pearson's r to mild normality violations in samples exceeding $N = 100$.

Table 3: Pearson's Bivariate Correlation: $PSS-10$ and AIMHS ($N = 149$)

Parameter	Value
Pearson's r	.537
Coefficient of Determination (r^2)	.288
Statistical Significance (p)	< .001
95% Confidence Interval	[.418, .637]
Degrees of Freedom	147
Effect Size (Cohen's benchmarks)	Moderate-to-Strong
Decision on H_0	Rejected

Significance threshold: $\alpha = .05$, two-tailed. CI computed via Fisher z -transformation.

The Pearson's correlation between $PSS-10$ scores and AIMHS scores was $r(147) = .537$, $p < .001$, 95% CI [.418, .637]. The null hypothesis ($H_0: \rho = 0$) is rejected; the alternate hypothesis ($H_1: \rho > 0$) is supported. The coefficient of determination ($r^2 = .288$) indicates that perceived stress accounts for approximately 28.8% of the variance in AI chatbot acceptance. According to Cohen's [22] benchmarks (small: $r = .10$ –.29; medium: $r = .30$ –.49; large: $r \geq .50$), the observed $r = .537$ constitutes a moderate-to-strong effect. The linear regression equation derived is: $AIMHS = 5.62 + (0.53 \times PSS-10)$.

D. Supplementary Analyses

Gender differences in $PSS-10$ scores: An independent-samples t -test comparing male ($n = 88$, $M = 20.9$, $SD = 6.1$) and female ($n = 58$, $M = 23.2$, $SD = 6.6$) students yielded $t(144) = 2.11$, $p = .037$, $d = 0.35$. Female students reported significantly higher perceived stress than male students. The effect size is modest; interpretation should account for social desirability differences in emotional expression across genders.

Academic stream differences in AIMHS scores: A one-way ANOVA yielded $F(2, 146) = 4.83$, $p = .009$, $\eta^2 = .062$. Post-hoc Tukey HSD comparisons indicated that Engineering/Technology students ($M = 18.4$, $SD = 3.8$) scored significantly higher than Arts/Commerce students ($M = 16.1$, $SD = 4.3$; mean difference = 2.3, $p = .008$). This reflects engineering students' greater baseline familiarity with AI tools, consistent with TAM2's social influence constructs.

AI usage status and stress levels: An independent-samples t-test comparing AI users ($n = 87$, $M = 24.3$, $SD = 5.9$) and non-users ($n = 62$, $M = 18.4$, $SD = 6.1$) yielded $t(147) = 5.89$, $p < .001$, $d = 0.97$ —a large effect. The finding that over half of AI users fell in the high-stress category compared to roughly one quarter of non-users powerfully contextualises the primary correlation finding.

Table 4: Summary of Supplementary Group Comparison Analyses

Comparison	Test	Statistic	p	Effect Size
Male vs. Female (PSS-10)	Independent t-test	$t(144) = 2.11$	.037	$d = 0.35$ (small-moderate)
Stream differences (AIMHS)	One-way ANOVA	$F(2,146) = 4.83$	.009	$\eta^2 = .062$ (small-moderate)
AI Users vs. Non-Users (PSS-10)	Independent t-test	$t(147) = 5.89$	$< .001$	$d = 0.97$ (large)

E. Qualitative Adoption Drivers

Table 5: AI Chatbot Adoption Drivers Among Confirmed Users ($n = 87$)

Adoption Driver	Frequency (%)	Theoretical Alignment
24/7 Accessibility	78%	TAM2 — Perceived Usefulness; Academic Time Poverty
Anonymity / Non-Judgment	72%	Online Disinhibition Effect; PCT — Stigma as Social Risk
Ease of Access	65%	TAM2 — Perceived Ease of Use
Free of Cost	58%	Socioeconomic Accessibility
Stigma Avoidance	45%	Log Kya Kahenge; Mental Health Privacy Paradox
Immediate Response	41%	Lazarus-Folkman: Emotion-Focused Coping
Conversational Quality	34%	ELIZA Effect; Cognitive Empathy

Participants could select multiple adoption drivers. Percentages reflect the proportion of AI users endorsing each driver.

Table 6: AI Platform Preferences Among Confirmed Users ($n = 87$)

AI Platform	% Users	Clinical Classification
ChatGPT (OpenAI)	55.1%	General-purpose LLM — unregulated for clinical use
Google Gemini	26.5%	General-purpose LLM — unregulated for clinical use
Other General LLMs	12.5%	General-purpose LLM — unregulated for clinical use
Wysa	5.9%	Clinically validated therapeutic application
Tele-MANAS / Other Validated Apps	0.0%	Government-endorsed; clinically validated

LLM = Large Language Model. An overwhelming 94.1% of AI-using students employ tools designed for productivity and creative generation—not clinical mental health intervention. The complete absence of Tele-MANAS usage is particularly striking given that it is a free, government-endorsed, clinically supervised service designed for the Indian population (accessible at 14416).

F. Integration and Discussion

The constellation of findings converges on a coherent and clinically urgent narrative. The primary correlation ($r = .537$, $p < .001$) establishes that perceived stress is a meaningful predictor of AI chatbot acceptance. The supplementary finding that AI users operate at substantially higher stress levels ($d = 0.97$) confirms that AI adoption is concentrated among the most distressed students.

The qualitative adoption driver data explain the mechanism through which stress translates into AI acceptance. Under conditions of high distress, TAM2's Perceived Usefulness and Ease of Use constructs are weighted against the specific costs of formal counselling in the Indian cultural context: scheduling friction, financial cost, and above all, the social cost of being identified as someone who is not coping. Against these costs, the AI chatbot's offering of immediacy, anonymity, and zero social exposure is not merely convenient—it is, for many students, the only viable option.

The Mental Health Privacy Paradox provides a culturally specific account of why this relationship is as strong as it is. In a cultural context where stigma constitutes the primary privacy risk, the reduction of social risk provided by AI anonymity functions as the primary adoption driver—not a secondary consideration. The 72% anonymity citation and 45% stigma avoidance citation are two articulations of the same underlying dynamic.

The Safety Paradox sits at the intersection of these findings: the most stressed students—those most in need of clinical support—are overwhelmingly using tools with no clinical design, no crisis detection, and no regulatory accountability. This represents the study's most important contribution to applied mental health policy.

V. CONCLUSION AND RECOMMENDATIONS

This study provides robust empirical evidence that perceived stress is a significant positive predictor of AI chatbot acceptance among college students in Bengaluru ($r = .537$, $p < .001$, $r^2 = .288$). The Safety Paradox—wherein the most clinically distressed students are disproportionately using the least clinically validated tools—is the defining challenge for mental health policy in Indian higher education.

A. For Higher Educational Institutions

Institutions should implement a Hybrid Care Architecture: a tiered system integrating AI as a Tier 1 triage and psychoeducation tool within a structured care pathway, with Tier 2 peer support and Tier 3 professional counselling. AI tools deployed within this architecture must be clinically validated, DPDPA 2023-compliant, and institutionally endorsed. Institutions should develop formal AI Mental Health Endorsement Policies distinguishing approved platforms (Wysa, Tele-MANAS) from general-purpose LLMs. Mental health literacy programs enabling students to distinguish evidence-based AI support from simulation are urgently needed.

B. For Policy Stakeholders

The zero uptake of Tele-MANAS represents a policy failure demanding urgent response. The Ministry of Health and Family Welfare and NIMHANS should commission a student-targeted re-launch of Tele-MANAS with a simplified user interface and active student ambassador programs in higher education institutions. The DPDPA (2023) creates an important regulatory lever: institutions endorsing AI mental health tools bear data fiduciary obligations, and sector-specific guidance and certification frameworks are needed.

C. For Clinical Practitioners

Mental health professionals in Indian higher education institutions should incorporate AI chatbot usage into clinical intake conversations. Given that AI adoption is concentrated among the most distressed students, disclosure of AI chatbot use may serve as a clinical indicator of elevated stress severity. Practitioners should avoid stigmatizing AI use while gently redirecting toward validated tools.

D. For Future Research

Longitudinal designs tracking cohorts across semesters would enable direct examination of causal direction. Experimental designs comparing mental health outcomes for AI-only, human counselling-only, and hybrid support conditions would provide causal evidence for clinical guidelines. Cross-cultural

comparative studies contrasting Bengaluru with Tier 2 cities and international populations would examine whether the Mental Health Privacy Paradox is context-specific or generalizable. Formal psychometric validation studies for the AIMHS in Indian populations represent an urgent priority.

E. Limitations

Key limitations include: (1) purposive convenience sampling limits representativeness, with engineering students overrepresented at 47.8%; (2) cross-sectional design precludes causal inference; (3) the AIMHS's limited cross-cultural validation for Indian populations; (4) binary AI usage classification cannot distinguish habitual use from single experimental interaction; and (5) absence of data on confounding variables including prior mental health diagnoses and personality traits.

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