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Use of Artificial Intelligence Chatbots for Emotional Support, User Perception and Emotional Reliance Among Undergraduate Healthcare Students in Rural South India

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Abstract:

- ***Background:***

Undergraduate healthcare students in India experience heavy academic pressure and exhausting hospital duties, yet rarely consult mental health professionals because of social stigma and fear of losing internal marks. Many students now turn to smartphone artificial intelligence (AI) chatbots late at night for private emotional comfort. This study assessed the prevalence of AI chatbot usage for emotional support, user perception, and emotional reliance among healthcare trainees in rural South India.

- ***Methods:***

A descriptive cross-sectional survey was conducted among 500 undergraduate students in Nursing, Medicine (MBBS), Allied Health Sciences, and Physiotherapy in Kuppam, Andhra Pradesh, using convenience sampling. Participants completed a validated self-administered questionnaire (Cronbach alpha = 0.71) covering sociodemographic variables, chatbot usage patterns, an 8-item Perception Scale (score range 8 to 40), and a 5-item Emotional Reliance Scale (score range 5 to 25). Data were analyzed using descriptive statistics, Pearson Chi-square tests, and Spearman rank correlation.

- ***Results:***

Out of 500 students, 36.60 percent (n = 183) actively used AI chatbots for emotional support, whereas 0.00 percent (n = 0) had ever consulted a human counselor or psychiatrist. Among active users, ChatGPT (74.86 percent) and WhatsApp Meta AI (17.49 percent) were most common, and 38.80 percent chatted daily. While 61.20 percent held a good perception (Mean = 30.05, SD = 6.27), 46.99 percent showed high emotional reliance (Mean = 16.78, SD = 5.10). High emotional reliance was significantly greater in male students than females (67.60 percent vs. 42.30 percent, Chi-square = 7.178, p = 0.028) and in commuting day scholars than hostellers (57.60 percent vs. 36.30 percent, Chi-square = 9.266, p = 0.010). Perception correlated positively with emotional reliance (Spearman rho = 0.630, p < 0.0001).

- ***Conclusion:***

Smartphone AI chatbots have completely replaced formal human counseling among surveyed rural healthcare students. Colleges must introduce confidential counseling and digital awareness programs to prevent unhealthy emotional dependency.

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Keywords: *Artificial Intelligence Chatbots; Emotional Support; Emotional Reliance; Healthcare Students; Nursing Education; Mental Health Stigma; Rural India.*

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I. INTRODUCTION

Undergraduate education in nursing, medicine, physiotherapy, and allied health sciences is widely considered one of the toughest academic paths a young person can take. Unlike peers in general university degree courses, healthcare students carry a double burden from their very first year: they must master a large theoretical syllabus while working long hours in hospital wards [1]. During hospital ward postings, young trainees witness severe illness, painful procedures, and patient deaths firsthand while completing daily clinical record books and preparing for strict practical and theory examinations. When a student faces such continuous pressure—a scolding from a clinical supervisor in front of patients, fear of making a medication error, or back-to-back hospital shifts—the brain's emotional alarm center (the amygdala) repeatedly triggers the sympathetic nervous system and the hypothalamic-pituitary-adrenal (HPA) axis [2]. Over months of sleepless duty shifts, this continuous hormone surge creates allostatic load—chronic wear and tear that impairs hippocampal memory consolidation, weakens prefrontal attention and decision-making, disturbs sleep architecture, and triggers low-grade systemic inflammation [2]–[4]. Clinically, this biological strain leads to academic burnout marked by emotional exhaustion, detachment from patients, and a painful sense of personal inadequacy [5], [6].

Around the world, epidemiological studies show that healthcare students suffer much higher rates of anxiety, depression, and burnout than age-matched peers in the general population. In a comprehensive global meta-analysis of 195 studies involving 129,123 medical students across 47 countries, Rotenstein et al. [7] found that 27.2% of students screened positive for depression or depressive symptoms and 11.1% experienced suicidal ideation during their training, yet only 15.7% of depressed medical students ever sought professional care. In low- and middle-income countries (LMICs) such as India, the gap between emotional distress and formal care is even wider [8], [9]. According to the National Mental Health Survey of India, the country has a treatment gap exceeding 80% for common mental health conditions, driven by a severe shortage of psychiatrists and clinical psychologists outside major metropolitan cities and by deep-seated social stigma [10].

Inside Indian medical, nursing, and allied health campuses, seeking help from a human counselor is blocked by strong institutional and cultural barriers [11], [12]. In a cross-sectional study of 425 undergraduate medical students in South India, Arun et al. [11] reported that 24.0% suffered from clinically significant depression or anxiety and 29.6% had elevated suicide risk, yet students strongly resisted visiting the psychiatry department. The reasons reported by Indian students mirror findings from Western medical schools [13], [14], but are sharpened by the close-knit hierarchy of Indian health colleges: students fear that teachers and classmates will see mental distress as a sign of personal weakness, worry that consulting a psychiatrist will lower their internal assessment marks or spoil their future career, and doubt whether campus consultations will remain confidential [11], [12]. In rural Indian teaching hospitals, students and faculty share the same campus; walking into the psychiatry clinic means being seen by classmates or grading professors, and daytime clinic hours (9:00 a.m. to 4:00 p.m.) clash with ward postings while emotional crises strike late at night.

Because human counseling feels inaccessible, students increasingly turn to smartphone artificial intelligence (AI) chatbots for comfort [15], [16]. Earlier scripted cognitive behavioral therapy (CBT) bots like Woebot and Tess reduced short-term distress in randomized trials [17]–[19], but fixed replies often felt robotic [20]. Since 2022, general-purpose large language models (LLMs)—such as OpenAI's ChatGPT, Meta AI built into WhatsApp and Instagram, and Google Gemini—have become widely used for personal emotional support despite being built for general productivity rather than therapy [15], [21]. In India, a recent youth report highlighted that nearly 57% of Indian young adults text AI chatbots to vent academic pressure, relationship worries, and family stress because the chatbot feels safe, does not shame them, and never informs their parents or teachers [22]. Recent reviews and qualitative studies among university and healthcare populations confirm that students appreciate AI chatbots for their 24/7 availability, instant replies during short ward breaks, zero financial cost, and freedom from social stigma [23], [24].

However, clinical psychologists and psychiatric researchers have recently warned that relying on unregulated, general-purpose generative AI for emotional support carries serious psychological risks [15], [25], [26]. Bockting et al. [15] cautioned that generative AI chatbots are designed to keep users engaged through flattering, affirming, people-pleasing replies—a behavior known as algorithmic sycophancy. Controlled experiments in Science by Cheng et al. [27] demonstrated that although users strongly prefer and trust sycophantic AI chatbots, interacting with such overly agreeable models reduces users' willingness to repair real-life interpersonal conflicts and fosters psychological dependence. Recent scoping reviews of LLM mental health harms [25] and AI companionship [26] show that unlike human friendships—which require patience and working through disagreements—chatbots offer friction-free intimacy. Daily venting to an endlessly validating bot can trigger emotional reliance, restlessness when offline, and withdrawal from real friends and family [25], [26], [28].

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Drawing on Dorothea Orem's Self-Care Deficit Nursing Theory [29] and Davis's Technology Acceptance Model (TAM) [30], we view this behavior as a compensatory process: when heavy clinical stress exceeds a student's coping capacity and campus stigma blocks human counseling (a self-care deficit), students adopt smartphone AI chatbots due to their ease of use and perceived secrecy, which provides immediate comfort but risks high emotional reliance. Therefore, this study was conducted among 500 undergraduate healthcare students in Kuppam, Andhra Pradesh, with four objectives: (1) to determine the prevalence and usage patterns of AI chatbots for emotional support compared with human counseling; (2) to evaluate students' perceptions of AI chatbots as an emotional support tool; (3) to measure the level of emotional reliance on AI chatbots; and (4) to examine how sociodemographic factors and perception scores relate to emotional reliance.

II. MATERIALS AND METHODS

➢ *Study Design and Setting*

A descriptive, observational cross-sectional survey was carried out in recognized healthcare educational institutions in Kuppam, Chittoor District, Andhra Pradesh, India. Kuppam is a rural and semi-urban town situated at the tri-state border of Andhra Pradesh, Karnataka, and Tamil Nadu. The educational campus—anchored by the PES College of Nursing and the PES Institute of Medical Sciences and Research (PESIMSR)—serves as a major regional training and tertiary healthcare hub for surrounding rural villages. Students enrolled here experience intensive classroom and bedside clinical training in a close-knit campus environment where independent, off-campus psychological counseling facilities are virtually absent. Field data collection was conducted over a planned three-month period between December 2025 and March 2026.

➢ *Participants and Sample Size Determination*

The target population comprised undergraduate students aged 18 to 35 years actively enrolled in four professional healthcare streams: Bachelor of Science in Nursing (B.Sc. Nursing), Bachelor of Medicine and Bachelor of Surgery (MBBS), Allied Health Sciences (AHS), and Bachelor of Physiotherapy (BPT). Students were eligible to participate if they were aged 18 to 35 years, had used or were currently using smartphone or web-based AI chatbots, were available during the data collection period, and provided written informed consent. Partially filled or incomplete questionnaires were excluded.

Sample size was estimated using the single-proportion prevalence formula, $n = Z^2 \times P(1 - P) / d^2$, where $Z = 1.96$ for a 95% confidence interval, $d = 0.05$ (5% margin of error), and $P = 0.57$ based on national survey data indicating that 57% of Indian youth use AI chatbots for emotional support [22]. This yielded a minimum required sample of 377 students. Accounting for a 10% non-response rate ($n_{adj} = 377 / [1 - 0.10] = 419$), the minimum target sample was 419. Using non-probability convenience sampling across academic cohorts and clinical batches, a total of N = 500 eligible undergraduate healthcare students completed the survey in full.

➢ *Research Instrument and Psychometric Validation*

Data were collected using a structured, four-part self-administered paper questionnaire developed in clear, accessible English. Content validity was established through independent review by a panel of subject experts from Community Health Nursing, Community Medicine, and Biostatistics. Prior to main data collection, the tool was pre-tested in a pilot sample outside the final study cohort; internal consistency reliability evaluated via the split-half method and Cronbach's alpha formula was r = 0.71, confirming satisfactory reliability and stability.

Section A recorded age, gender, course (Nursing, MBBS, AHS, BPT), academic year (I–IV Year, Internship), and residential status (commuting day scholar vs. campus hosteller). Section B asked all 500 students whether they had ever consulted a human mental health professional and whether they actively used AI chatbots for emotional support; for active users (n = 183), it recorded preferred platform, usage frequency, and session duration. Section C (Perception of AI Chatbots as Emotional Support Scale) consisted of eight items scored on a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree; total score range = 8–40), evaluating perceived comfort, ease of 24/7 access, privacy, freedom from faculty judgment, patience, and perceived helpfulness in calming stress, classified into Poor (8–18), Moderate (19–29), and Good Perception (30–40). Section D (Emotional Reliance Scale) comprised five 5-point Likert items (range = 5–25) aligned with recent AI dependency indicators [25], [26]: feeling emotionally dependent on the bot, feeling restless or anxious when offline, preferring the bot over talking to friends or family, treating the bot as a primary companion when lonely, and relying on it to regulate mood, grouped into Low (5–11), Moderate (12–18), and High Emotional Reliance (19–25).

➢ *Ethical Considerations and Data Collection Procedure*

Formal ethical clearance was obtained from the Institutional Research Committee (IRC) and the Institutional Human Ethics Committee (IHEC) of PESIMSR, Kuppam, and administrative permission was secured from the respective college principals. All procedures complied with the Declaration of Helsinki. Students were approached in their classrooms during non-examination hours, briefed on the study objectives, and assured that their responses would remain completely anonymous and have zero impact on their internal marks. Written informed consent was obtained from every participant, and completed questionnaires (25–30 minutes) were identified solely by numerical codes.

➢ *Statistical Analysis*

Survey data were coded into Microsoft Excel and analyzed using IBM SPSS Statistics. Descriptive statistics—frequencies (n), percentages (%), means (M), and standard deviations (SD)—summarized demographic variables, prevalence rates, usage patterns, and scale scores. Pearson's Chi-square (χ^2) test of independence tested associations between sociodemographic characteristics and categorical levels of perception and emotional reliance among active users (n = 183). Spearman's rank-order correlation coefficient (ρ) evaluated the monotonic association between total perception scores and total emotional reliance scores, with statistical significance set at $p < 0.05$.

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III. RESULTS

➢ *Sociodemographic Profile and Prevalence of Support-Seeking*

All 500 participants completed the questionnaire (mean age = 20.85 ± 2.14 years, range = 18–25; Table 1). Most were female (84.00%, n = 420) and enrolled in B.Sc. Nursing (51.80%, n = 259), followed by MBBS (18.60%, n = 93), Allied Health Sciences (17.20%, n = 86), and BPT (12.40%, n = 62). Fourth-year (36.60%, n = 183) and second-year (27.20%, n = 136) students formed the largest cohorts, and the sample was evenly split between commuting day scholars (50.20%, n = 251) and campus hostellers (49.80%, n = 249). Across the total sample (N = 500), 36.60% (n = 183) actively used AI chatbots on their smartphones for emotional support and stress relief, whereas 0.00% (n = 0)—not a single student out of 500—had ever consulted a human mental health professional, college counselor, psychologist, or psychiatrist (Table 1).

➢ *AI Chatbot Usage Patterns, Perception Levels, and Emotional Reliance*

Among active users (n = 183; Table 2), ChatGPT was preferred by 74.86% (n = 137), followed by WhatsApp/Instagram Meta AI (17.49%, n = 32), Google Gemini (6.01%, n = 11), and Perplexity AI (0.55%, n = 1); none used dedicated therapy bots like Woebot. Overall, 38.80% (n = 71) chatted daily and 27.87% (n = 51) weekly, while 47.54% (n = 87) had brief sessions under 5 minutes and 40.98% (n = 75) chatted for 5 to 15 minutes. On the Perception Scale (range 8–40), the mean score was 30.05 ± 6.27, with 61.20% (n = 112) showing Good perception, 33.33% (n = 61) Moderate, and 5.46% (n = 10) Poor perception (Table 2). However, on the Emotional Reliance Scale (range 5–25), the mean score was 16.78 ± 5.10: nearly half of active users (46.99%, n = 86) showed High Emotional Reliance (score 19–25), 32.24% (n = 59) showed Moderate reliance, and only 20.77% (n = 38) maintained Low reliance.

Table 1 Sociodemographic Characteristics and Prevalence of Support-Seeking Behaviors Among Healthcare Students (N = 500)

Variable	Category	Frequency (n)	Percentage (%)
Gender	Female	420	84.00%
	Male	80	16.00%
Course of Study	B.Sc. Nursing	259	51.80%
	MBBS (Medicine)	93	18.60%
	Allied Health Sciences (AHS)	86	17.20%
	Bachelor of Physiotherapy (BPT)	62	12.40%
Year of Study	I Year	30	6.00%
	II Year	136	27.20%
	III Year	67	13.40%
	IV Year	183	36.60%
	Internship	84	16.80%
Residential Status	Day Scholar (Commuting)	251	50.20%
	Hosteller (Campus Dormitory)	249	49.80%
Used AI Chatbot for Emotional Support	Yes (Active Users)	183	36.60%
	No	317	63.40%
Sought Human Mental Health Professional Help	Yes	0	0.00%
	No	500	100.00%

Mean Chronological Age of Participants = 20.85 ± 2.14 Years (Range 18–25 Years). Total Sample N = 500.

Table 2 AI Chatbot Usage Patterns, Perception Levels, and Emotional Reliance Levels Among Active Users (n = 183)

Domain / Construct	Category / Score Range	Frequency (n)	Percentage / M ± SD
Preferred AI Platform	ChatGPT	137	74.86%
	Meta AI (WhatsApp / Instagram)	32	17.49%
	Google Gemini	11	6.01%
	Perplexity AI	1	0.55%
Frequency of Usage	Daily (Code 1.0)	71	38.80%
	Weekly (Code 3.0)	51	27.87%
	Occasionally (Code 4.0)	38	20.77%
	2–3 Times a Week (Code 2.0)	22	12.02%
Average Session Duration	Less than 5 minutes (Code 1.0)	87	47.54%
	5 to 15 minutes (Code 2.0)	75	40.98%
	More than 15 minutes (Code 3.0)	17	9.29%
Perception Level (Range: 8–40)	Good Perception (30–40)	112	61.20%
	Moderate Perception (19–29)	61	33.33%
	Poor Perception (8–18)	10	5.46%
Perception Total Score	Continuous Scale (8–40)	183	30.05 ± 6.27
Emotional Reliance (Range: 5–25)	High Emotional Reliance (19–25)	86	46.99%
	Moderate Emotional Reliance (12–18)	59	32.24%

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	Low Emotional Reliance (5–11)	38	20.77%
Emotional Reliance Total Score	Continuous Scale (5–25)	183	16.78 ± 5.10

Analyses Restricted to Active Emotional-Support Chatbot Users (n = 183). Minor Item Non-Response Occurred on Platform (n = 2), Frequency (n = 1), and Duration (n = 4).

➢ *Sociodemographic Associations with Perception Levels*

Perception levels did not differ significantly by gender ($\chi^2 = 1.819$, $p = 0.403$) or course of study ($\chi^2 = 8.611$, $p = 0.197$; Table 3). However, perception was significantly associated with academic year ($\chi^2 = 19.311$, $p = 0.013$)—peaking in I Year (77.80% Good), III Year (70.60%), and IV Year (70.30%) compared with II Year (38.10%)—and with residential status ($\chi^2 = 17.641$, $p < 0.001$), where commuting day scholars reported much higher Good perception than campus hostellers (76.10% vs. 46.20%).

➢ *Sociodemographic Associations with Emotional Reliance and Correlation Analysis*

Emotional reliance was significantly associated with gender ($\chi^2 = 7.178$, $p = 0.028$) and residential status ($\chi^2 = 9.266$, $p = 0.010$; Table 4). High Emotional Reliance was substantially more common in male users than females (67.60% vs. 42.30%) and in commuting day scholars than hostellers (57.60% vs. 36.30%), whereas course ($\chi^2 = 6.519$, $p = 0.368$) and academic year ($\chi^2 = 11.657$, $p = 0.167$) were non-significant. Cross-tabulation of human professional help-seeking against AI chatbot usage (N = 500) and emotional reliance levels (n = 183) yielded a constant statistic of $\chi^2 = 0.000$ ($p = 1.000$) because 100% of students had never consulted a human professional (Table 5). Furthermore, Spearman's rank-order correlation analysis (Table 5) demonstrated a strong, positive, and highly significant correlation between total perception score and total emotional reliance score ($\rho = +0.630$, $p < 0.0001$).

Table 3 Association Between Sociodemographic Variables and Perception Levels Toward AI Chatbots Among Active Users (n = 183)

Variable	Category	Poor n (%)	Moderate n (%)	Good n (%)	χ^2	p-value
Gender	Female	8 (5.40%)	53 (35.60%)	88 (59.10%)	1.819	0.403
	Male	2 (5.90%)	8 (23.50%)	24 (70.60%)		
Course of Study	Allied Health (AHS)	0 (0.00%)	4 (17.40%)	19 (82.60%)	8.611	0.197
	BPT	2 (11.10%)	5 (27.80%)	11 (61.10%)		
	MBBS	3 (7.70%)	17 (43.60%)	19 (48.70%)		
	B.Sc. Nursing	5 (4.90%)	35 (34.00%)	63 (61.20%)		
Year of Study	I Year	0 (0.00%)	2 (22.20%)	7 (77.80%)	19.311	0.013*
	II Year	1 (2.40%)	25 (59.50%)	16 (38.10%)		
	III Year	2 (5.90%)	8 (23.50%)	24 (70.60%)		
	IV Year	4 (6.20%)	15 (23.40%)	45 (70.30%)		
	Internship	3 (8.80%)	11 (32.40%)	20 (58.80%)		
Residential Status	Day Scholar	4 (4.30%)	18 (19.60%)	70 (76.10%)	17.641	< 0.001**
	Hosteller	6 (6.60%)	43 (47.30%)	42 (46.20%)		

*χ^2 = Pearson Chi-Square Statistic. *p < 0.05. **p < 0.001.*

Table 4 Association Between Sociodemographic Variables and Emotional Reliance Levels on AI Chatbots Among Active Users (n = 183)

Variable	Category	Low n (%)	Moderate n (%)	High n (%)	χ^2	p-value
Gender	Female	34 (22.80%)	52 (34.90%)	63 (42.30%)	7.178	0.028*
	Male	4 (11.80%)	7 (20.60%)	23 (67.60%)		
Course of Study	Allied Health (AHS)	2 (8.70%)	7 (30.40%)	14 (60.90%)	6.519	0.368
	BPT	3 (16.70%)	7 (38.90%)	8 (44.40%)		
	MBBS	11 (28.20%)	15 (38.50%)	13 (33.30%)		
	B.Sc. Nursing	22 (21.40%)	30 (29.10%)	51 (49.50%)		
Year of Study	I Year	0 (0.00%)	4 (44.40%)	5 (55.60%)	11.657	0.167
	II Year	13 (31.00%)	16 (38.10%)	13 (31.00%)		
	III Year	5 (14.70%)	10 (29.40%)	19 (55.90%)		
	IV Year	10 (15.60%)	21 (32.80%)	33 (51.60%)		
	Internship	10 (29.40%)	8 (23.50%)	16 (47.10%)		
Residential Status	Day Scholar	13 (14.10%)	26 (28.30%)	53 (57.60%)	9.266	0.010*
	Hosteller	25 (27.50%)	33 (36.30%)	33 (36.30%)		

*χ^2 = Pearson Chi-Square Statistic. *p < 0.05.*

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Table 5 Cross-Tabulation of Human Help-Seeking with AI Chatbot Usage (N = 500) and Emotional Reliance (n = 183), and Spearman Correlation

Analytical Comparison	Subgroup / Metric	Outcome Distribution / Value	Test Statistic	p-value
Human Help vs. AI Chatbot Use (N = 500)	Never Sought Human Help (n = 500)	Uses AI: 183 (36.60%) | No AI: 317 (63.40%)	$\chi^2 = 0.000$	1.000
Human Help vs. AI Chatbot Use (N = 500)	Sought Human Help (n = 0)	Uses AI: 0 (0.00%) | No AI: 0 (0.00%)		
Human Help vs. AI Reliance (n = 183)	Never Sought Human Help (n = 183)	Low: 38 (20.77%) | Mod: 59 (32.24%) | High: 86 (46.99%)	$\chi^2 = 0.000$	1.000
Human Help vs. AI Reliance (n = 183)	Sought Human Help (n = 0)	Low: 0 (0.00%) | Mod: 0 (0.00%) | High: 0 (0.00%)		
Perception vs. Emotional Reliance (n = 183)	Total Perception (30.05) vs. Reliance (16.78)	Strong positive monotonic association	Spearman ρ = +0.630	< 0.0001**

*Constant Zero Cell Counts for Human Professional Help-Seeking Reflect 100% Avoidance of Formal Psychiatric or Counseling Services. **p < 0.0001.*

IV. DISCUSSION

This study provides primary empirical evidence on how undergraduate healthcare trainees in rural South India use general-purpose AI chatbots for emotional coping. Across 500 Nursing, MBBS, Allied Health, and Physiotherapy students in Kuppam, we found complete avoidance of human mental health professionals (0.00%) alongside active emotional-support chatbot use by 36.60% of students, near-exclusive reliance on ChatGPT (74.86%) and WhatsApp Meta AI (17.49%), a strong positive correlation between perceived comfort and emotional reliance (ρ = +0.630, with 46.99% showing High Reliance), and heightened vulnerability among male students and commuting day scholars.

- *Total Avoidance of Human Counseling Versus Digital Substitution*

The finding that 0 out of 500 healthcare students had ever consulted a psychologist, psychiatrist, or college counselor—while 183 students actively confided their emotional struggles to an AI chatbot—is a wake-up call for health professions educators. Globally, Rotenstein et al. [7] showed that over 84% of depressed medical students do not seek professional help, and prior Indian studies have consistently documented strong resistance to psychiatric consultations among medical and nursing undergraduates [11], [12]. In a rural residential campus like Kuppam, however, help-seeking avoidance reached 100%. On a rural Indian teaching hospital campus, psychiatrists and psychologists also serve as teaching and examination faculty. Students fear that visiting the campus clinic will invite peer gossip, label them as weak, and lower their practical marks [11], [13], [14], while daytime ward shifts prevent clinic visits. When human support feels unsafe or unavailable, the smartphone AI chatbot becomes a secret, 24/7 digital refuge—not merely supplementing human care, but completely replacing it [15], [22].

- *Dominance of General-Purpose LLMs Over Dedicated Mental Health Apps*

Notably, 98.36% of active users relied on general-purpose LLMs—ChatGPT (74.86%), WhatsApp Meta AI (17.49%), and Google Gemini (6.01%)—rather than clinical bots like Woebot or Tess [18], [19]. Consistent with recent reviews [15], [21], students prefer LLMs for their natural, human-like fluency over rigid scripts [20], and because ChatGPT and WhatsApp are already installed on their phones for daily study and messaging [30]. Nearly half of our active users (47.54%) chatted for less than 5 minutes at a time, and 38.80% used the bot daily, showing that students use LLMs for quick 'micro-venting' between hospital rounds or late at night without having to download a separate mental health app that a roommate might spot on their phone screen [24]. Yet, as Bockting et al. [15] and Diel et al. [25] warn, these general-purpose commercial models were never validated as psychiatric tools; they lack clinical supervision, can generate false or sycophantic reassurance, and often fail to trigger crisis interventions when a user expresses severe hopelessness or self-harm.

- *The Comfort-Reliance Paradox and Algorithmic Sycophancy*

While 61.20% of active users held a Good perception of AI chatbots (M = 30.05 ± 6.27)—valuing their privacy, infinite patience, and soothing replies, much like university students in Oman and East Asia [16], [23]—nearly half (46.99%) simultaneously exhibited High Emotional Reliance (M = 16.78 ± 5.10). Moreover, Spearman correlation revealed a strong positive association between perception and emotional reliance (ρ = +0.630, $p < 0.0001$). In simple terms, the more a student feels that the AI chatbot is a kind, understanding, and non-judgmental friend, the more emotionally dependent they become on it. Recent behavioral and psychiatric studies explain the mechanism behind this 'digital trap' [15], [25]–[27]. Commercial LLMs are trained using human feedback to be agreeable, flattering, and unconditionally validating—a property Cheng et al. [27] term sycophantic AI behavior. Cheng et al. [27] showed that sycophantic AI responses make users feel validated but reduce their willingness to resolve real interpersonal conflicts and foster dependency. Once exhausted trainees get used to friction-free comfort at 2:00 a.m., talking to real roommates or parents feels tiring, breeding restlessness when offline and social withdrawal [25], [26], [28].

- *Vulnerability of Male Healthcare Students and Commuting Day Scholars*

Our subgroup analyses identified two demographic groups at particularly high risk for emotional reliance: male students and commuting day scholars. Although female students made up the majority of the nursing-heavy sample, male chatbot users displayed a significantly higher rate of High

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Emotional Reliance than female users (67.60% vs. 42.30%, p = 0.028). This finding directly corroborates the scoping review by Diel et al. [25], which identified male sex as a significant correlate of LLM chatbot dependence. In Indian society, boys are socialized from childhood not to cry, complain, or show emotional vulnerability in front of friends or family [22]. Whereas female students in college hostels frequently share their clinical worries and exam stress with female roommates, male healthcare students often feel ashamed to admit emotional pain to male peers. Once male students discover that they can pour out their deepest fears to a private smartphone chatbot without any loss of masculine pride, they form a much heavier emotional bond with the tool.

Equally important, commuting day scholars showed both a significantly higher Good perception (76.10% vs. 46.20%, p < 0.001) and a significantly higher rate of High Emotional Reliance (57.60% vs. 36.30%, p = 0.010) than campus hostellers. In rural Kuppam, day scholars commute long hours on crowded buses from nearby villages, return home to household chores, and lack college peers at night, whereas hostellers can vent with roommates after ward shifts. Deprived of evening peer support, commuters rely heavily on smartphone chatbots during bus rides and late-night study. Likewise, the significant peak in Good perception among I Year (77.80%), III Year (70.60%), and IV Year (70.30%) students reflects the intense adjustment stress of first-year hospital entry and the heavy clinical and university examination pressures of the senior years.

➢ *Clinical, Educational, and Policy Implications*

These findings have direct implications for nursing and medical education, clinical practice, and public health policy. Compassionate patient care requires healthcare professionals who can tolerate interpersonal discomfort, listen empathetically to suffering patients, and work collaboratively in clinical teams [6], [31]. If nearly half of student chatbot users become emotionally reliant on sycophantic algorithms and pull back from real human conversations, their bedside empathy and emotional resilience may suffer [26]. We recommend four concrete actions for healthcare colleges and policymakers: (1) establish truly confidential, off-ward student counseling centers staffed by independent psychologists who do not teach or grade students, paired with anonymous evening tele-counseling so students can seek human help after duty hours without fear of losing marks; (2) introduce structured 'Digital and AI Mental Health Literacy' workshops during first-year orientation and final-year clinical transitions, teaching students how LLM sycophancy works, why general-purpose chatbots are unsafe during mental health crises, and how to spot warning signs of emotional dependency [25], [26]; (3) build campus peer-support lounges and gender-sensitive mentorship groups specifically reaching out to commuting day scholars and male students; and (4) align institutional policies with international calls for independent scientific auditing, adverse-event reporting, and strict data-privacy safeguards for publicly available generative AI systems [15], [32].

V. LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

Several limitations warrant note. Convenience sampling within a single rural educational hub in Kuppam limits generalizability to metropolitan universities; the cross-sectional design precludes causal inference between perception and reliance; and self-report measures were used without concurrent clinical interviews or diagnostic scales (such as the PHQ-9 or GAD-7). Future research should conduct multi-center longitudinal cohort studies across urban and rural Indian healthcare institutions, tracking students across their training years to examine how daily LLM chatbot use affects clinical empathy, real-world social networks, and academic retention, and testing safe 'human-in-the-loop' campus triage models [15], [23].

VI. CONCLUSION

Among undergraduate healthcare students in rural South India, smartphone AI chatbots such as ChatGPT and WhatsApp Meta AI have become a private, round-the-clock emotional refuge, completely replacing formal human counseling services (36.60% active AI use vs. 0.00% human professional help-seeking). Although students widely perceive these AI tools as comforting, secret, and non-judgmental listeners, nearly half of active users (46.99%) have developed high emotional reliance, with male students and commuting day scholars facing the greatest vulnerability. Healthcare universities and nursing leaders must recognize this hidden digital shift—not by shaming students for seeking comfort, but by removing the stigma and grading fears that block human counseling, building peer support for commuters and male trainees, and guiding future healthcare professionals to use artificial intelligence wisely without replacing genuine human connection.

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