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Research Article

Artificial Intelligence as a Coping Strategy Among University Students: A Quantitative Investigation into Emotional Relief, Cognitive Clarity, and the Perceived Limitations of AI-Assisted Self-Regulation

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Abstract

The adoption of generative AI systems in particular large language models such as ChatGPT has expanded at a pace that extends far beyond academic or professional use cases. University students are increasingly turning to AI in emotionally challenging situations, using it as a conversational partner, reflective medium, and source of relief. The present study investigates whether this behavior can be conceptualized as a functional coping strategy within the framework of transactional stress theory [1]. A sample of N = 150 university students (M = 23.4 years, SD = 3.1) completed scales measuring AI coping, emotional relief, cognitive clarity, perceived stress, and ambivalence toward AI use. Results reveal significant positive associations between AI coping and emotional regulation (r = .62, p < .01) and cognitive clarity (r = .68, p < .01), alongside a negative association with perceived stress (r = -.31, p < .01). Multiple regression analysis identified AI coping as the strongest predictor of emotional relief (β = .58, p < .01, R^2 = .42). Analysis of variance confirmed dose-dependent effects by usage intensity. At the same time, the data reflect structural ambivalence: AI is perceived as emotionally inauthentic and as an incomplete substitute for human relationships. Findings are discussed in relation to coping theory, digital health research, and the psychotherapy relationship literature.

Keywords: Artificial intelligence, Coping, Stress regulation, Emotional relief, University students, ChatGPT, Digital mental health, Self-regulation

1. Introduction

Psychological distress among university students is not a peripheral phenomenon but a globally documented, structurally entrenched problem. International surveys consistently demonstrate that anxiety disorders, depressive episodes, and chronic stress occur at substantially higher rates among students than in similarly aged general population samples [2-4]. Stallman (2010) found that more than 80 percent of Australian students had experienced clinically significant distress symptoms in the twelve months preceding the survey [5]. Evidence from German-speaking countries paints a comparable picture: performance pressure, examination anxiety, social isolation, and financial insecurity form a burden structure that is often amplified by the transition into higher education [6,7].

Despite demonstrably high levels of need, access to professional psychological support remains structurally constrained. Gulliver et al. identify stigma, limited awareness of available services, long waiting times, and personal shame as central barriers to help-seeking among young adults [8]. Hunt and Eisenberg show that even students with diagnosable conditions frequently do not seek or receive professional help [9]. This gap between need and utilization creates space for alternative coping strategies and it is precisely into this space that generative artificial intelligence has entered since 2022 with remarkable levels of adoption.
Following the public release of ChatGPT in November 2022, a new form of human-machine interaction has emerged that extends far beyond information retrieval or text generation. Users report turning to AI systems to discuss personal problems, articulate emotional burdens, process conflicts, and seek guidance during difficult decision-making situations [10,11]. Whether and how this behavior qualifies as a psychological coping strategy constitutes a theoretically and empirically underexplored research gap.

The present study addresses this gap directly. Its goal is to

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theoretically situate generative AI use as coping behavior among university students, to examine it empirically, and to characterize its effects and limitations. AI use is approached not as pathology or naive technophilia, but as a behavior that can and must be analyzed within established coping frameworks. Equally important are the boundaries of this strategy: which dimensions of psychological support can AI not structurally provide, and what implications follow for prevention, counseling, and higher education policy?

2. Theoretical Background

2.1 Coping as a Psychological Construct

In the stress literature, coping refers to the cognitive, emotional, and behavioral efforts a person makes to manage demands appraised as exceeding their available resources [1]. The transactional stress model does not treat stress as an objective feature of a situation, but as the outcome of a two-stage appraisal process. Primary appraisal evaluates the situation for its threat potential; secondary appraisal assesses the coping resources available to meet that threat. Subjective stress emerges from the discrepancy between perceived threat and estimated coping capacity [12].

Lazarus and Folkman distinguish between problem-focused coping, which targets direct change in the stressful situation, and emotion-focused coping, which targets the regulation of the emotional response [1]. Carver et al. extended this model to include additional dimensions such as seeking social support, positive reframing, and venting, which have since found broad application in empirical research [13]. In a later revision of the model, Folkman and Moskowitz emphasize the role of positive emotions in the coping process: even when a situation cannot be resolved, experiencing a sense of control, meaning, or temporary relief can sustain psychological resilience [14].

The use of social support as a coping resource is among the most consistently documented protective factors against stress-related psychological distress [15,16]. What matters is not only the objective availability of social networks, but the subjective experience of being heard, understood, and offered new perspectives. These are precisely the functions that students are increasingly attributing to AI systems, which raises the question of whether and under what conditions machine-mediated interaction can functionally serve this role.

2.2. Emotion Regulation and Cognitive Clarity

Coping is closely intertwined with the broader construct of emotion regulation. Gross defines emotion regulation as the processes by which individuals influence which emotions they have, when they have them, and how they experience and express those emotions [17]. His process model distinguishes antecedent-focused strategies such as cognitive reappraisal from response-focused strategies such as expressive suppression. Cognitive reappraisal is considered the more adaptive of the two, as it modulates the emotional response at its source and is associated with better long-term outcomes [18].

In the context of AI-assisted interaction, a central question is whether articulating distressing thoughts to an AI system activates similar cognitive and emotional processes as writing in a journal or speaking with a trusted person. Pennebaker demonstrated across a series of influential studies that the structured expression of emotionally significant experiences in written form even without feedback produces significant effects on mood, immune function, and physical health [19]. This expressive writing paradigm suggests that the act of verbalization alone can initiate a therapeutically beneficial process, irrespective of whether the addressee is human or machine.

Nolen-Hoeksema identified rumination repetitive, passive dwelling on negative experiences as a central mechanism through which mood disorders become chronic [20] . An intervention that enables individuals to interrupt this cycle through structured reflection, perspective-taking, or externalization of the thought stream can be functionally classified as adaptive coping. AI systems that respond to input in a structured manner and formulate alternative perspectives may be well positioned to serve precisely this interruption function.

2.3. AI in Digital Mental Health Care

The integration of AI and chatbot technologies into health-related contexts is not new, but the availability of generative models has introduced a qualitative shift. Early chatbot applications such as ELIZA already demonstrated that individuals are willing to share emotionally significant content with machine interlocutors a phenomenon Weizenbaum himself found troubling [21]. More recent systems such as Woebot, a cognitive-behavioral therapy-based messaging chatbot, have been examined in randomized trials. Fitzpatrick et al. reported significant reductions in depression and anxiety symptoms following two weeks of Woebot use among university students in comparison to a control condition [22].

Vaidyam et al. distinguish in a systematic review between informational chatbots, monitoring systems, and therapeutically oriented conversational agents, and argue that effectiveness depends strongly on the degree of personalization, dialogic quality, and theoretical grounding [11]. Abd-Alrazaq et al. found in a meta-analysis that users appreciate AI chatbots in health contexts primarily for their availability, non-judgmental stance, and patience characteristics that compare favorably with human helpers in qualitative terms, while emotional depth and genuine understanding are consistently cited as structural deficits [23].

Several psychological mechanisms explain why individuals are willing to share emotionally relevant content with AI. Suler describes the online disinhibition effect: in computer-mediated communication, social inhibitions are reduced because anonymity, invisibility, and the absence of a physically present interlocutor lower the threshold for self-disclosure [24]. Joinson replicated this finding and demonstrated that

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self-disclosure in computer-mediated communication is systematically higher than in face-to-face settings [25]. Lucas et al. showed experimentally that individuals report more psychological symptoms to an interview computer than to a human interviewer even when aware that they are interacting with a machine [26]. This finding has direct relevance for understanding why AI systems are experienced as less intimidating than professional help.

2.4. University Students as a Vulnerable and Relevant Target Group

University students occupy a developmental phase characterized by multiple simultaneous transitions and demands. The move from school to higher education often involving relocation, the construction of new social networks, financial independence, and academic performance pressures constitutes a vulnerability-generating context [27,28]. At the same time, students represent a technology-fluent population with high media engagement, for whom the integration of digital tools into daily life is routine.

Auerbach et al. drawing on the WHO World Mental Health Surveys, report that over one third of students across 19 countries show clinically significant mental disorders, yet only a fraction of those affected access professional help [2]. This gap between need and utilization makes students a particularly important target group for low-threshold digital support formats. AI systems that are accessible around the clock, free of charge, and non-judgmental correspond structurally to precisely the needs of this population.

3. Research Questions and Hypotheses

The following research questions derive from the theoretical framework and the state of existing research: First, to what extent do university students use generative AI systems as a coping strategy for psychological distress? Second, what associations exist between AI coping and emotional relief, cognitive clarity, and perceived stress? Third, does AI coping function as a significant predictor of emotional relief when controlling for usage frequency and gender? Fourth, do levels of emotional relief differ as a function of AI usage intensity? Fifth, how do students appraise the limitations of AI-supported emotional assistance?

The following hypotheses are derived from the theoretical considerations and empirical findings reviewed above: H1: AI coping is positively and significantly associated with emotional relief and cognitive clarity. H2: AI coping is negatively and significantly associated with perceived stress. H3: AI coping makes a significant contribution to the prediction of emotional relief beyond usage frequency and gender. H4: Students with higher AI usage intensity report significantly greater emotional relief than those with lower usage. H5: Students perceive a lack of genuine empathy and the incomplete substitutability of human relationships as the central limitations of AI support.

4. Method

4.1. Participants

A total of N = 150 university students from various institutions participated in the study. The sample comprised 68 male participants (45.3%), 80 female participants (53.3%), and 2 participants identifying as non-binary (1.3%). Mean age was M = 23.4 years (SD = 3.1, range: 18–42 years). By field of study, participants were distributed across Psychology (n = 52, 34.7%), Social Sciences (n = 38, 25.3%), Business and Economics (n = 30, 20.0%), and other disciplines (n = 30, 20.0%). A total of 112 participants were enrolled in a bachelor's program (74.7%) and 38 in a master's program (25.3%). Regarding AI usage frequency, 42 participants reported using AI daily (28.0%), 71 several times per week (47.3%), and 37 infrequently (24.7%). Participation was voluntary and anonymous. Recruitment proceeded via institutional notice boards, social media channels, and direct outreach in course settings.

4.2. Measures

AI Coping Scale (newly constructed). A newly developed scale was used to assess AI-assisted coping behavior, theoretically grounded in the COPE inventory (Carver et al., 1989) and established operationalizations of emotion regulation (Gross & John, 2003). The scale covers facets including organizing thoughts with AI assistance, expressing emotions toward AI systems, reducing stress through AI conversations, and gaining new perspectives. Internal consistency was excellent (Cronbach's α = .89). Item-level means ranged from M = 3.45 for expressing emotions (SD = 0.94) to M = 4.12 for gaining perspectives (SD = 0.76), yielding a total scale score of M = 3.79 (SD = 0.63).

Emotional Relief. This scale captures the subjective experience of relief, calm, and emotional regulation following AI use (α = .86, M = 3.58, SD = 0.71). Cognitive Clarity assesses the degree of cognitive order and structure that participants experience through AI interaction (α = .83, M = 3.74, SD = 0.68). Perceived Stress was measured using an adapted version of the Perceived Stress Scale (PSS), a well-validated instrument with broad international norms (α = .88, M = 3.21, SD = 0.82) [29]. The Ambivalence Scale captures critical and ambivalent appraisals of AI use as a coping resource (α = .81, M = 3.02, SD = 0.77). All scales used a five-point Likert format (1 = does not apply at all to 5 = fully applies).

4.3. Data Analysis

Statistical analyses were conducted using IBM SPSS Statistics 29. Bivariate associations between scales were examined via Pearson correlations. A multiple linear regression analysis using the enter method was conducted to predict emotional relief; predictors included AI coping, usage frequency, and gender (coded as a dummy variable). Group differences by usage intensity were examined via one-way analysis of variance (ANOVA) with subsequent Tukey post-hoc tests. The significance threshold was set at α = .05. Effect sizes are reported as Cohen's f^2 for regression analyses and η^2 for group comparisons.

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5. Results

5.1. Descriptive Statistics and Scale Scores

The central scale scores present a consistent picture: university students use AI systems to a measurable degree as a coping resource. The AI Coping Scale total score was M = 3.79 (SD = 0.63), indicating clearly above-average endorsement on the five-point scale. The subscale Gaining New Perspectives yielded the highest mean within the instrument (M = 4.12, SD = 0.76), while Expressing Emotions received the lowest endorsement (M = 3.45, SD = 0.94). This pattern is theoretically coherent: cognitive clarification processes appear more readily transferred to AI than emotional self-disclosure. Among perceived advantage items, round-the-clock availability received the highest rating in the entire study (M = 4.52), followed by fast assistance (M = 4.41) and absence of judgment (M = 4.34). Perceived disadvantages centered on no real conversation (M = 4.11) and lack of genuine empathy (M = 3.88).

5.2. Correlation Analyses

All bivariate correlations were statistically significant. AI coping correlated strongly and positively with emotional relief ($r = .62$, $p < .01$) and cognitive clarity ($r = .68$, $p < .01$). The negative association with perceived stress was moderate in magnitude ($r = -.31$, $p < .01$). Emotional relief and cognitive clarity were also strongly intercorrelated ($r = .59$, $p < .01$), and both showed significant negative associations with stress (relief: $r = -.54$, $p < .01$; clarity: $r = -.47$, $p < .01$). Table 1 presents the full intercorrelation matrix. These findings fully support H1 and H2.

Variable	1	2	3	4
1. AI Coping	—			
2. Emotional Relief	.62**	—		
3. Cognitive Clarity	.68**	.59**	—	
4. Perceived Stress	-.31**	-.54**	-.47**	—

Note. ** $p < .01$

Table 1: Intercorrelation Matrix of Central Variables (Pearson r, N = 150)

5.3. Regression Analysis

The regression model including AI coping, usage frequency, and gender as predictors was statistically significant and explained 42 percent of the variance in emotional relief ($R^2 = .42$, $F(3, 146) = 35.17$, $p < .001$). The effect size ($f^2 = .72$) is classified as large [30]. AI coping was the strongest individual predictor ($\beta = .58$, $p < .01$). Usage frequency made an additional significant contribution ($\beta = .21$, $p < .05$), while gender did not reach statistical significance ($\beta = .04$, n.s.). These findings support H3: AI coping is the dominant predictor of emotional relief even after controlling for usage frequency and gender. The comparatively weaker contribution of usage frequency suggests that it is not primarily how often AI is used, but the nature and depth of the coping-oriented interaction, that drives the relief effect.

5.4. Group Comparisons by Usage Intensity (ANOVA)

The one-way ANOVA revealed a significant main effect of usage intensity on emotional relief, $F(2, 147) = 11.24$, $p < .001$, $\eta^2 = .13$. Tukey post-hoc tests indicated significant differences between all three groups. The effect size $\eta^2 = .13$ is classified as medium in the social sciences (Cohen, 1988). Table 2 summarizes the group comparisons. This dose-dependent pattern supports H4 and is theoretically meaningful: it suggests that the association between AI use and emotional relief cannot be explained by selection effects alone, but is associated with an increasingly intensive pattern of use over time.

Group	n	Relief (M)
Infrequent	37	3.12
Moderate	71	3.54
Frequent	42	3.98

Note. $F(2, 147) = 11.24$, $p < .001$, $\eta^2 = .13$. Tukey post-hoc tests: all pairwise group differences statistically significant.

Table 2: Emotional Relief by AI Usage Intensity (One-Way ANOVA, N = 150)

5.5. Perceived Advantages and Disadvantages

The item-level analysis of perceived advantages and disadvantages produced a differentiated picture that supports H5. The three most highly endorsed advantage items constant availability (M = 4.52), fast assistance (M = 4.41), and freedom from judgment (M = 4.34) correspond precisely to the usage motives documented in the digital health literature [8,23]. On the disadvantage side, no real conversations achieved the second highest rating in the entire survey (M = 4.11), surpassed only by constant availability. Lack of genuine empathy was also rated highly (M = 3.88), while superficial responses received a comparatively moderate rating (M = 3.42).

6. Discussion

6.1.AI as a Functional Coping Resource

The central findings of this study are unambiguous: university students use AI systems to a significant degree as a coping strategy, and this usage is robustly associated with both emotional relief and cognitive clarity. These findings extend a growing literature documenting AI-assisted interventions as effective supports for psychological distress [11,22]. The particularly strong association between AI coping and cognitive clarity (r = .68) is interpretable through Pennebaker's cognitive processing theory: rendering diffuse emotional content explicit in language imposes a cognitive structuring that relieves distress independently of the nature of the addressee [19]. AI systems that offer structured follow-up prompts and formulate alternative framings may amplify this effect. Gross would classify this as successful cognitive reappraisal a reframing of the situation through altered informational processing that reduces negative affect [17].

That AI coping is a substantially stronger predictor of emotional relief than mere usage frequency (β = .58 vs. β = .21) carries theoretical importance: it suggests that it is not primarily how often AI is consulted, but how that is, the quality of coping-oriented engagement that drives the relief effect. This resonates with Carver et al.'s argument that functional coping is characterized by its function rather than its frequency [13]. The dose-dependent pattern in the ANOVA simultaneously suggests that more intensive use over time may refine the capacity for coping-oriented interaction.

6.2. The Online Disinhibition Effect and Its Implications

The most highly endorsed advantage constant availability combined with freedom from judgment corresponds precisely to the online disinhibition effect described by Suler [24]. The absence of social consequences, the sense of anonymity, and the non-reciprocal structure of the interaction (AI expects nothing in return) substantially lower the threshold for self-disclosure. This structural property of AI systems explains why they are experienced as less intimidating than professional help even when the subjective assessment of content quality is lower.

At the same time, this structural feature is double-edged. The low threshold that invites engagement may also enable an uncritical intensification of use that avoids confrontation with real interpersonal conflicts. Turkle describes in this context a growing preference for connection without the risks of genuine relationship a pattern that relieves distress in the short term but may erode relational capacity over time [31].

6.3. Structural Limitations: The Empathy Gap

The highest disadvantage rating no real conversations (M = 4.11) is remarkable in its magnitude: it exceeds the total scores on several of the measured scales and is nearly equivalent to the highest advantage rating. The sample thus simultaneously perceives AI as substantially relieving and as fundamentally insufficient. This paradox is clinically significant.

Wampold demonstrates in a comprehensive meta-analysis that the therapeutic relationship the experience of connectedness, understanding, and shared purpose is among the strongest predictors of psychotherapeutic outcome, independent of the technique employed [32]. Norcross identifies empathy, genuineness, and unconditional positive regard as the central relationship-shaping variables [33]. Grawe adduces neuropsychological evidence that the experience of genuine connectedness in therapy activates fundamentally different neural processes than purely cognitive information processing [34]. AI can structure information and articulate perspectives; it cannot generate affective resonance grounded in authentic understanding.

Reeves and Nass demonstrate that humans tend to treat computers as social actors and respond to them as they would to human interlocutors a phenomenon they term the Media Equation [35]. Yet even when this response feels subjectively real, it is grounded in cognitive heuristic rather than genuine relatedness. The emotional relief experienced through AI interaction is thus real without necessarily resting on a symmetrical relational experience. Relief and healing are not synonymous.

6.4. Implications for Practice and Higher Education Policy

The present findings carry several practical implications. University counseling services should actively integrate AI-assisted coping resources as low-threshold supplements within their service structures, rather than dismissing or ignoring them. Stepped-care models could establish AI-supported self-help tools as an initial tier, with pathways into professional counseling for those who require it. The ambivalence data also suggest that students themselves already possess a differentiated awareness of the limitations of AI-supported assistance. Psychoeducational offerings that sharpen this awareness while simultaneously fostering effective AI use could further improve outcomes. Finally, the association between usage frequency and relief points toward the potential value of training coping competencies in AI use — not merely expanding access to AI, but educating students in the nature of beneficial engagement (digital mental health literacy).

6.5. Limitations

Several limitations must be considered when interpreting the findings. All data are based on self-report, which cannot exclude social desirability bias and subjective distortion. The cross-sectional design precludes causal inference; whether AI use generates emotional relief, or whether less distressed students make more intensive use of AI, cannot be distinguished. Possible selection effects — specifically the overrepresentation of technology-fluent individuals or those with stronger baseline self-regulation capacity — are methodologically uncontrolled. Future studies should employ longitudinal designs to clarify causal directions and should measure the specific AI functions and interaction patterns used, enabling empirically grounded differentiation between informational and emotionally reflective usage modes.

7. Conclusion

The present study demonstrates that generative AI systems fulfill a measurably effective coping function among university students. The findings replicate and extend the digital health literature and situate AI-assisted coping within a regression-analytical explanatory model for the first time using a purpose-built, reliable scale. AI coping is the dominant predictor of emotional relief, effects follow a dose-dependent logic, and users themselves demonstrate a nuanced awareness of both the strengths and structural limitations of this resource.

AI thus functions as a low-threshold, continuously available coping strategy with significant short-term effects on emotional regulation and cognitive clarity, while exhibiting a structural limitation in the perceived depth of interpersonal support. This duality genuine relief effects alongside emotional incompleteness positions AI as an important but necessarily supplementary element within a pluralistic coping ecology. It does not replace the psychotherapeutic relationship, but it can ease, bridge, and lower the path toward it and in an underserved university mental health landscape, that contribution is more consequential than it might initially appear.

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