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Original Article

LARGE LANGUAGE MODELS AND EMOTIONAL REGULATION OF UNIVERSITY STUDENTS IN PESHAWAR, KHYBER PAKHTUNKHWA

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ABSTRACT

In the digital age, LLMs have significantly transformed students' academic practices and impact emotional experiences. The present study aimed to investigate the impact of instrumental and relational dependency on emotion regulation strategies among university students. A quantitative, cross-sectional research design was employed. The sample consisted of 380 university students, recruited through convenience sampling from multiple universities. Participants completed a demographic information sheet, the Dual-Dimensional Scale of Instrumental and Relationship Dependency on Large Language Models (LLM-D12), and the Emotion Regulation Questionnaire (ERQ), which measures habitual use of cognitive reappraisal and expressive suppression. Data were analyzed using descriptive statistics, multivariate regression, and independent-samples *t*-tests using SPSS version 23. Findings revealed that instrumental dependency does not significantly predict cognitive reappraisal or expressive suppression. Additionally, relational dependency showed a significant negative prediction effect on cognitive reappraisal and expressive suppression, suggesting that greater relationship dependency was associated with lower use of these emotion regulation strategies. Furthermore, non-significant gender differences were found across instrumental dependency, relational dependency, cognitive reappraisal, and expressive suppression. The findings underscore the need for balanced, responsible, and psychologically informed approaches to AI integration that support academic performance while preserving students' emotional growth and independence in an increasingly AI-driven educational environment.

I. INTRODUCTION

Large Language Models (LLMs)—conversational artificial intelligence systems such as OpenAI's ChatGPT, Google's Gemini, Anthropic's Claude, and Microsoft's Copilot—have seen unprecedented adoption in higher education (Luna, 2023; Yankouskaya et al., 2025). Powered by hundreds of millions to billions of parameters, these systems provide students with real-time feedback, detailed explanations, and time-management support (Pitts et al., 2025). Consequently, LLMs are increasingly embedded in everyday academic routines (Labadze et al., 2023). University students represent a critical demographic for examining the psychological implications of LLM integration. Emerging adulthood is marked by heightened academic stress, identity formation, and evolving autonomy (Stöhr et al., 2024), requiring robust emotion regulation (ER) to manage workload and performance expectations (Iuga &

David, 2024). While structured use of LLMs can enhance academic performance and self-efficacy, overreliance risks compromising critical thinking and cognitive engagement (Pitts et al., 2025; Zhai et al., 2024). Furthermore, students are increasingly forming affective bonds with AI chatbots in search of motivational and emotional reinforcement (Kim et al., 2025). As conversational AI blurs the boundary between cognitive scaffolding and emotional companionship, educational psychologists face both opportunities and challenges (Zhai et al., 2024). LLM dependency—the habitual or excessive reliance on conversational agents that yields maladaptive outcomes (Huang et al., 2024)—manifests in two primary dimensions:

The reliance on LLMs for cognitive, decision-making, and academic tasks, such as summarizing literature, drafting text, and writing code (Labadze et al., 2023; Yankouskaya et al., 2025). Although instrumental use alleviates short-term academic pressure, excessive dependency may undermine long-term psychological resilience and intrinsic motivation (Zvinodashe Revesai, 2025). The tendency to perceive LLMs as empathetic, companion-like entities rather than purely functional tools (Yankouskaya et al., 2025). This dimension involves seeking social support, reassurance, and emotional interaction from AI systems designed with simulated empathy and contextual memory (Kim et al., 2025). Emotion regulation (ER) refers to the processes by which individuals influence which emotions they experience, when they experience them, and how these emotions are expressed (Gross, 1988). Gross categorizes these mechanisms into antecedent-focused strategies (e.g., cognitive reappraisal) and response-focused strategies (e.g., expressive suppression). In higher education, effective ER protects against academic burnout and fatigue while fostering academic achievement (Iuga & David, 2024; Klimova, 2025). Emerging adulthood is characterized by maturing emotional control capacities. Early interventions suggest AI chatbots can alter psychological functioning by reducing symptoms of anxiety and depression in young adults. Help-seeking behaviors and technology adoption vary by gender. Female students tend to report higher relational AI engagement for emotional reassurance (Kim et al., 2025), whereas male students predominantly exhibit instrumental reliance for technical problem-solving (Zvinodashe Revesai, 2025). Stressors, workloads, and emotional demands differ across fields of study and between undergraduate and postgraduate levels, shaping how students utilize AI tools to regulate academic stress (Stöhr et al., 2024).

II. LITERATURE REVIEW

The rapid expansion of artificial intelligence (AI)-driven educational tools has transformed academic life while introducing subtle psychological and behavioral shifts. Although research highlights the pedagogical benefits of Large Language Models (LLMs)—including personalized learning, content generation, and enhanced efficiency (Labadze et al., 2023)—concerns are mounting regarding student dependency patterns. As AI becomes a primary medium for intellectual and emotional engagement, questions arise regarding its influence on autonomous thought and emotion regulation (ER). Educational psychologists emphasize that overreliance on AI tools can induce cognitive offloading, wherein mental effort is minimized through continuous external assistance (Zhai et al., 2024). Such reliance risks disrupting not only self-regulated learning but also the affective processes supporting academic persistence. Beyond cognitive implications, the emotional consequences of AI integration warrant empirical attention. Studies on social chatbots and LLMs indicate that students frequently develop emotional attachments to these systems, leveraging them for companionship or affective regulation (Kim et al., 2025). This transition from interpersonal to technological regulation presents a critical challenge: as AI tools increasingly penetrate academic and personal domains, they may reshape fundamental self-regulatory capacities.

The higher-education context amplifies these vulnerabilities. University students navigate academic stress, social isolation, and identity transitions that heighten susceptibility to digital dependencies (Iuga & David, 2024). While students rely on AI for both functional and emotional support, few empirical studies have examined how instrumental and relational dependencies interact to influence ER outcomes. This lack of integrated evidence forms the critical gap the present research addresses. Characterized by reliance on LLMs for academic and cognitive support, instrumental use can reduce immediate stress by simplifying tasks, but it may also hinder the development of frustration tolerance and problem-focused coping (Zvinodashe Revesai, 2025). Outsourcing cognitive challenges bypasses essential opportunities for emotional learning, such as managing uncertainty or failure (Pitts et al., 2025). Consequently, high instrumental dependency may correlate with lower implementation

of adaptive strategies such as cognitive reappraisal and self-reflection. Conversely, intentional, moderate AI usage may serve as a buffer against stress, promoting emotional balance during academic overload (Zhai et al., 2024).
Relational dependency, defined as emotional reliance on AI for companionship and affective comfort, impacts emotion regulation more directly. Emotionally attached users often engage in co-regulation with AI, using affective exchanges to soothe stress or loneliness (Kim et al., 2025). Although these interactions provide temporary relief by mimicking interpersonal support networks, excessive relational dependency risks fostering avoidance of human support and weakening autonomous emotional control. Developmental stage influences ER capacity. Emerging adults typically display less consistent use of adaptive regulation strategies than older individuals, suggesting that age may moderate students' responses to reliance on external technology (Fitzpatrick et al., 2017). Gender-based variations in regulation strategies are widely documented; women generally report greater use of cognitive reappraisal, whereas men more frequently employ expressive suppression. These patterns suggest gender may dictate whether students utilize LLMs primarily as cognitive aids or emotional supports. Disciplinary contexts present distinct stress profiles, coping expectations, and workload demands, influencing both students' emotional challenges and their patterns of technological reliance.

Theoretical Framework

Interpersonal Dependency Theory: Interpersonal dependency theory posits that individuals vary in the degree to which they rely on external agents for support, guidance, and decision-making, even when independent functioning is attainable (Bornstein, 2011). This multidimensional construct encompasses autonomous assertion, social self-confidence, and emotional reliance. Individuals exhibiting high interpersonal dependency frequently seek external reassurance to navigate stress, uncertainty, and emotional challenges (Bornstein, 2011). Applied to educational settings, students who demonstrate instrumental or relational reliance on Large Language Models (LLMs) may leverage these systems not only to complete academic tasks but also to manage psychological distress. For example, a student experiencing academic anxiety might turn to an LLM for reassurance or cognitive reframing of anxious thoughts. This dynamic illustrates how reliance on an artificial external agent can directly shape a student's coping mechanisms and emotion regulation (ER) processes.

Interpersonal Emotion Regulation Theory: Interpersonal Emotion Regulation (IER) theory proposes that individuals frequently regulate their affective states through interactions with external agents rather than relying solely on internal cognitive strategies (Zaki & Williams, 2013). IER operates through two primary pathways: response-dependent regulation, wherein emotional outcomes depend on the specific feedback of the social agent, and response-independent regulation, wherein the act of engaging or expressing emotion itself facilitates regulation regardless of the specific response (Zaki & Williams, 2013). In higher education, students exhibiting relational dependency may utilize LLMs for emotional venting, reassurance, or cognitive reappraisal. Emotional relief may occur either through the AI's generated response (response-dependent) or simply through the interactive process of articulating feelings to the interface (response-independent). Over time, habitual engagement with conversational agents may structurally alter how students regulate their emotions.

Process Model of Emotion Regulation: Gross's (1998) Process Model of Emotion Regulation conceptualizes ER as a series of strategies deployed at distinct points along the emotion-generative process: situation selection, situation modification, attentional deployment, cognitive change, and response modification. These strategies are broadly categorized into antecedent-focused forms(e.g., cognitive reappraisal, situation modification), which intervene before an emotional response is fully activated, and response-focused forms (e.g., expressive suppression), which modulate an emotion after it has developed. This model provides a structural framework for understanding how LLM engagement influences emotional processing in digital learning environments: Instrumental Dependency primarily intersects with antecedent-focused strategies, as students utilize LLMs to reframe academic obstacles, reduce cognitive load, or strategically avoid emotionally taxing tasks. Relational Dependency primarily influences response-focused strategies, as students turn to LLMs to seek validation, comfort, or affective modulation following distressing academic experiences. The present study addresses the growing integration of artificial intelligence, specifically Large Language Models (LLMs), into university students' academic and personal routines. In recent years, these platforms have become essential for student learning, communication, and problem-solving (Pitts et al., 2025). While LLMs offer clear benefits—such as efficiency, accessibility, and convenience—there are rising concerns regarding how frequent engagement shapes psychological functioning. An urgent yet underexplored issue is how reliance on these systems influences students' capacity to regulate emotions under academic stress.

This study holds significant value at the intersection of educational technology and psychological well-being. Beyond functional academic tasks, students increasingly turn to LLMs for companionship, emotional validation, and inspiration. This dual engagement—encompassing both instrumental and relational dependencies—may alter students' perceived autonomy, self-efficacy, and coping capacities. By investigating these dependency dimensions in relation to cognitive reappraisal and expressive suppression, this study seeks to determine whether LLM engagement fosters adaptive functioning or subtly diminishes psychological independence and resilience. Despite the rapid proliferation of LLMs, empirical research connecting specific AI dependency patterns to ER strategies among higher education students remains scarce. Existing literature predominantly focuses on social media addiction, generalized digital tool use, or broad AI acceptance, leaving the psychological nuances of conversational, highly responsive LLM reliance largely unexamined. The present study addresses this critical gap.

Objectives

1. To assess the impact of instrumental and relational dependency on cognitive reappraisal and expressive suppression of university students.
2. To examine the gender differences between instrumental dependency, relational dependency, cognitive reappraisal, and expressive suppression among university students.

Hypotheses

1. Instrumental and relational dependency will significantly predict cognitive reappraisal and expressive suppression among university students.
2. There will be significant gender differences between instrumental dependency, relational dependency, cognitive reappraisal, and expressive suppression among university students.

III. METHOD

Participants

The total sample was calculated using a sample size calculator, which showed 380 students. Data were collected from different universities in Peshawar conveniently. Convenient sampling was used. Participants were reached out to base on inclusion criteria and ease of access. Gender-based qualities were Male = 186; Female = 194 from semesters 1st to 8th in B.S level and semesters 1st to 4th in M.S level, and early vs mid adulthood age groups. The inclusion criteria; 1) Only university students were included in the study, and 2) Participants must use LLMs to some extent. The exclusion criteria were school or college students and employees in any sector were excluded from the study.

Measures

[I] Dual-Dimensional Scale of Instrumental and Relationship Dependency on Large Language Models – LLM-D12: The Dual-dimensional scale of instrumental and relationship dependency on Large Language Models (LLM-D12 consists of a 12-item questionnaire originally developed by Yankouskaya et al. (2025). The scale comprises two subscales: Instrumental Dependency (6 items) and Relationship Dependency (6 items), which reflect the extent to which individuals rely on LLMs as a tool and social patterns, respectively. Items are rated on a 6-point Likert Scale ranging from 1 (Strongly disagree) to 6 (Strongly agree), with one item reverse-scored. The reliability of this scale has been supported by recent research (Yankouskaya et al., 2025), reporting Cronbach's alpha values for Instrumental Dependency as 0.84 and for Relationship dependency is 0.91, indicating strong internal consistency for both scales. Also, it relates to the other measures like trust in AI and general technology use, which supports the validity of this scale. **[II]** Emotion Regulation Questionnaire: The Emotion Regulation Questionnaire consists of 10 items is originally developed by Gross and John (2003). The scale comprises two subscales- cognitive reappraisal (six items) and expressive suppression (four items)- which assess individual differences in the habitual use of these two emotion regulation strategies. Items are rated on a 7-point Likert Scale ranging from 1 (Strongly disagree) to 7 (Strongly agree). Its construct validity has been confirmed through factor analysis, supporting that the two subscales do not overlap with each other or other unrelated constructs. The reliability of the scale has been supported by the research (Preece et al., 2021), which reported a Cronbach's alpha value ≥.75, indicating strong internal consistency of the scale.

Procedure

Initially, the researchers visited various universities in Peshawar city for the purpose of collecting quantitative data from students. Before data collection, the researchers provided clear instructions to the concerned university authorities and individual students, respectfully seeking their permission to participate in the study. A total of 380 university students who met the study's inclusion criteria were enrolled as participants. This sample comprised 186 males and 194 females. Participants were thoroughly informed that all the collected data would be maintained with strict confidentiality and their participation would not entail any physical or psychological harm. Participants were also explicitly requested to cooperate fully and to complete the standardized questionnaires honestly. Upon the completion of the data collection. The researchers carefully entered all completed questionnaires into SPSS Version 23 for comprehensive statistical analysis.

Ethical Consideration

Informed consent was obtained from the participants, and privacy and confidentiality were ensured regarding the matters. The researchers assured the participants that participation in the study is totally voluntary and there is no physical or psychological risk at any point in the study.

IV.RESULTS

Table I: Descriptive of Demographic Variables (N = 380)

Variables	Categories	*n*	%	M	SD
Age				22.46	2.89
Gender					
	Male	186	48.9		
	Female	194	51.1		
Educational Level					
	BS	243	63.94		
	MS	137	36.04		

Note. n = frequency

Table II: Psychometric Properties of Study Variables (N=380)

Variables	K	α	M	SD	Range Min	Range Max	Skew
Instrumental Dependency	6	.91	21.22	6.15	7.00	35.00	-.00
Relationship Dependency	6	.91	20.31	6.25	6.00	34.00	.10
Cognitive Reappraisal	6	.79	24.57	5.16	13.00	37.00	.00
Expressive Suppression	4	.82	14.62	4.66	4.00	27.00	.04

Note. M = Mean, SD= Standard deviation, K = number of items, Skew = Skewness, and Kurt= kurtosis.

Table 2 shows psychometric properties for the scales used in the present study. The Instrumental Dependency scale and Relationship Dependency scale demonstrated excellent internal consistency α= .91 (>.70), each respectively. The mean score of participants was 21.22 with a SD of 6.15 and skewness value (-.00) for Instrumental Dependency scale and for Relationship Dependency scale, the mean score was 20.31 with a SD of 6.25 and skewness value (.10). Similarly, The Croncbach's α for the Cognitive Reappraisal was α= .79 (>.70) and Expressive Suppression was α= .82 (>.70) which indicates good internal consistency.

Table III: Multiple Regression Analysis Predicting Cognitive Reappraisal from Dependency Dimensions (N = 398)

Predictors	B	SE B	β	t	p	95% CI
Instrumental Dependency	-0.03	0.05	-.04	-0.62	.53	[-0.13, 0.07]
Relationship Dependency	-0.11	0.05	-.13	-2.17	.03	[-0.21, -0.01]

For cognitive reappraisal, the overall regression model was statistically significant, F (2, 395) = 3.39, p = .035, explaining approximately 1.7% of the variance in cognitive reappraisal (R^2 = .017). Relationship dependency emerged as a significant negative predictor of cognitive reappraisal, B = −0.11, SE = 0.05, β = −.13, t = −2.17, p = .031, indicating that higher relationship dependency was associated with reduced use of cognitive reappraisal strategies. However, instrumental dependency did not significantly predict cognitive reappraisal, B = −0.03, SE = 0.05, β = −.04, p = .535.

Table IV: Multiple Regression Analysis Predicting Expressive Suppression from Dependency Dimensions (N = 398)

Predictors	B	SE B	β	t	p	95% CI
Instrumental Dependency	-0.02	0.05	-.03	-0.42	.67	[-0.12, 0.08]
Relationship Dependency	-0.13	0.05	-.17	-2.78	.00	[-0.22, -0.04]

For expressive suppression, the regression model was also significant, F (2, 395) = 5.88, p = .003, accounting for 2.9% of the variance (R^2 = .029). Relationship dependency significantly and negatively predicted expressive suppression, B = −0.13, SE = 0.05, β = −.17, t = −2.78, p = .00. Conversely, instrumental dependency was not a significant predictor of expressive suppression, B = −0.02, SE = 0.05, β = −.03, p = .67. Overall, the findings suggest that relationship dependency is a stronger predictor of emotion regulation patterns than instrumental dependency, with higher relationship dependency being associated with lower levels of both cognitive reappraisal and expressive suppression.

Table V: Gender Differences on Instrumental Dependency, Relationship Dependency, Cognitive Reappraisal and Expressive Suppression (N=380)

	Male (n = 186)	Female (n = 194)			
Variables	M(SD)	M(SD)	t(378)	*P*	Cohen's d
Instrumental Dependency	21.09(6.06)	21.36(6.25)	-.42	.67	-
Relationship Dependency	20.28(5.93)	20.34(6.56)	-.08	.93	-
Cognitive Reappraisal	24.37(5.36)	24.76(4.97)	-.74	.45	-
Expressive Suppression	14.46(4.50)	14.76(4.83)	-.62	.53	-

Table 5 shows that there are non-significant mean differences between males and females in instrumental dependency, t (378) = −0.42, p = .6 or relationship dependency t (378) = −0.08, p = .93. Similarly, no significant differences were observed between males and females in cognitive reappraisal, t (378) = −0.74, p = .45, or expressive suppression, t (378) = −0.62, p = .53.

V. DISCUSSION

The present study aimed to investigate the relationship between the instrumental and relationship dependencies on emotion regulation among university students, using a sample of 380 individuals. The findings were analyzed through descriptive statistics, Pearson correlation coefficients, and independent-samples t-tests to explore the psychometric strengths of scales, relationships among variables, and demographic differences. Table 1 presents the demographic characteristics of the study participants (N=380). The mean age of the participants was 22 years (SD= 2.89), indicating that the sample primarily consisted of young adults. Regarding gender distribution, 186 participants (48.9%) were male, and 194 participants were female, reflecting a nearly equal representation of both genders in the sample. Participants were drawn from diverse academic fields. The largest proportion belonged to

Computer Science (n = 142, 37.4%), followed by Psychology (n = 90, 23.7%), English (n= 60, 15.8%), MLT (n= 51, 13.4% and Business (n = 37, 9.7%). In terms of educational level, the majority of participants were enrolled in BS programs (n = 297, 28.2%), while 83 participants (21.8%) were enrolled in MS programs.

Table 2 presents the descriptive statistics and psychometric properties of all study variables. Instrumental Dependency scale consists of 6 items and demonstrated excellent internal consistency (Cronbach's α =.91). Participants reported a mean score of 21.22 (SD = 6.15) with scores ranging from 7 to 35. The skewness value (-.00) indicates a symmetrical distribution of scores. Similarly, the Relationship Dependency scale consists of 6 items and indicates excellent internal consistency (Cronbach's α =.91). The mean score was 20.31(SD = 6.25) with scores ranging from 6 to 34. The skewness value (.10) suggested that the distribution is approximately normal. Similarly, for the Emotion Regulation Questionnaire, Cognitive Reappraisal consists of 6 items and showed good internal consistency (Cronbach's α =.79). The mean score was 24.57(SD = 5.16) with scores ranging from 13 to 37. The skewness value (.00) indicates a perfectly symmetrical distribution. Likewise, Expressive Suppression consists of 4 items and demonstrated good reliability (α =.82). Participants obtained a mean score of 14.62 (SD = 4.66) with scores ranging from 4 to 27. The skewness value (.04) suggests a near-normal distribution. Overall, Skewness values for all variables were within acceptable limits, indicating that the data were approximately normally distributed.

Table 3 and 4 revealed a significant negative prediction effect of relationship dependency on cognitive reappraisal as the p is calculated as less than .05, while instrumental dependency does not significantly predicted the cognitive reappraisal and expressive suppression dimensions of emotional regulation as the p was recorder greater than .05.This suggests that reliance on LLMs for instrumental support does not appear to be directly related to individual's use of emotion regulation strategies, which rejects the hypothesis that students with higher instrumental dependency are less likely to use emotion regulation strategies. The findings are inconsistent with existing literature (Zvinodashe Revesai, 2025). Relationship dependency, however, showed a small but significant negative prediction effect on cognitive reappraisal, $B = -.11$, $p < .05$, and on expressive suppression as well, $B = -.13$, $p < .01$. These results indicate the individual with higher emotional reliance on LLMs tend to report slightly lower use of emotion regulation strategies, which supports the hypothesis suggesting that greater relationship dependency was associated with lower use of these emotion regulation strategies. These findings are consistent with existing literature (Pitts et al., 2025).

As shown in Table 5, the gender difference in instrumental dependency was not significant, $t(378) = -0.42$, $p = .6$, for Male and Female participants, who reported comparable levels of instrumental reliance on LLMs. Similarly, no significant differences were found in relationship dependency, $t(378) = -0.08$, $p = .93$, suggesting that emotional reliance on LLMs does not differ meaningfully between males and females in the present sample. With respect to emotion regulation strategies, the results also revealed no significant gender differences in cognitive reappraisal, $t(378) = -0.74$, $p = .45$, or expressive suppression, $t(378) = -0.62$, $p = .53$. Although females reported slightly higher mean scores on both strategies compared to males, the differences were small and statistically non-significant.

Implications

The significant negative prediction of relational dependency on cognitive reappraisal and expressive suppression suggests that emotional reliance on Large Language Models (LLMs) may erode students' capacity for autonomous emotional processing and self-regulation. Instrumental engagement with LLMs appears to be a safe and academically beneficial practice when integrated appropriately into task-oriented learning. Conversely, relational dependency poses specific risks to emotional independence and psychological resilience, particularly during high-stress academic periods. Higher education institutions and educators can leverage these empirical distinctions to design AI-integrated curricula that maximize academic utility while safeguarding students' emotional and developmental growth. The lack of significant gender differences indicates that the psychological and emotional impacts of LLM dependency are broadly comparable across male and female students within university settings.

Recommendations and Suggestions

The findings of this study offer several actionable insights for higher education administrators, policy makers, and educators: Educational policy makers should formulate clear, responsible AI usage frameworks that recognize the pedagogical utility of Large Language Models (LLMs) while mitigating the psychological risks associated with prolonged dependency. Universities should actively promote balanced AI adoption, framing LLMs as complementary learning tools rather than substitutes for critical thinking, autonomous problem-solving, and independent emotional coping. Academic institutions should implement structured psychoeducational workshops focused on fostering adaptive emotion regulation (ER) strategies—such as cognitive reappraisal, stress tolerance, and reflective coping—to reduce reliance on external digital aids during academic distress. Future studies should utilize longitudinal or experimental paradigms to establish causal links between LLM dependency and ER outcomes, tracking how patterns of AI reliance evolve and influence long-term emotional development. Research should incorporate additional psychological variables—such as emotional intelligence, psychological resilience, loneliness, adult attachment styles, and general self-efficacy—to identify specific individual vulnerabilities to instrumental and relational AI dependencies.

VI.CONCLUSION

The methodology of this research was robust in design and implementation, ensuring valid, ethical and comprehensive data collection and analysis. The use of standardized psychometric tools and statistical rigor allowed clear testing of hypothesis, with significant findings, some supporting the primary and secondary hypothesis while others rejecting. Results of this study confirms a strong positive relationship between instrumental and relationship dependency, suggesting that practical reliance on LLMs may gradually extend into emotional reliance, reflecting an integrated pattern of technological engagement among university students. However, the findings provide a more nuanced understanding of how these forms of dependency relate to emotional functioning. Instrumental dependency showed no significant association with cognitive reappraisal or expressive suppression, indicating that using LLMs as academic or problem-solving tools does not inherently undermine or enhance students' emotion regulation capacities. This challenges assumptions that frequent technological reliance necessarily weakens emotional coping mechanisms. In contrast, relationship dependency demonstrated small but statistically significant negative associations with both cognitive reappraisal and expressive suppression. Although the effect sizes were modest, these findings suggest that greater emotional reliance on LLMs may be linked with slightly reduced engagement in adaptive emotion regulation strategies. This pattern raises important theoretical considerations: emotional dependency on artificial intelligence may reflect a compensatory mechanism, where students externalize aspects of emotional processing rather than actively regulating emotions internally. While the relationships are not strong, they signal potential psychological implications that warrant careful attention.

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