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Large Language Model–Based Intervention for Emotion Regulation and Rumination Among University Students: A Quasi-Experimental Study

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ABSTRACT

Objective: This study evaluated the effectiveness of a large language model–based intervention in improving emotion regulation and reducing rumination among university students.

Methods and Materials: This quasi-experimental controlled study used a pretest–posttest design with a three-month follow-up. Thirty university students were assigned to an intervention group (n = 15) or a control group (n = 15). The intervention group received eight structured sessions delivered through ChatGPT, focusing on emotional awareness, cognitive restructuring, mindfulness, stress management, problem-solving, and prevention of ruminative relapse. The control group received no intervention. Data were collected using the Emotion Regulation Questionnaire and the Ruminative Responses Scale. Analyses included paired t-tests, ANCOVA, and repeated-measures ANOVA.

Findings: In the intervention group, rumination decreased from 50.73 ± 12.45 at pretest to 35.80 ± 9.80 at posttest ($t = 17.39$, $p < 0.001$), while emotion regulation increased from 46.33 ± 6.51 to 55.20 ± 5.59 ($t = -16.91$, $p < 0.001$). ANCOVA showed significant between-group effects for rumination ($F = 14.75$, $p = 0.001$) and emotion regulation ($F = 11.82$, $p = 0.002$). Repeated-measures analysis confirmed significant time × group interactions for rumination ($F = 16.4$, $p < 0.001$, $\eta^2 = 0.47$) and emotion regulation ($F = 11.5$, $p < 0.001$, $\eta^2 = 0.35$), with effects maintained at three-month follow-up.

Conclusion: The large language model–based intervention significantly reduced rumination and improved emotion regulation among university students. Ethically guided AI-based interventions may support accessible student mental health care.

Keywords: Artificial Intelligence, Emotion Regulation, Rumination, Students, Mental Health.

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Introduction

Emotion regulation and rumination are key psychological processes that play a crucial role in the mental health of university students (Blanke et al., 2022). Studies have shown that heightened rumination and difficulties in regulating emotions are associated with various psychological disorders, including anxiety, depression, and reduced social and academic functioning (Clamora et al., 2024; Marques et al., 2023). In contrast, strengthening emotion regulation skills can enhance emotional stability, improve academic achievement, and promote psychological well-being (Ni & Jia, 2025).

Rumination, defined as a repetitive pattern of negative thinking, often intensifies negative emotions and prolongs anxiety and psychological distress (Nolen-Hoeksema et al., 2008). Among students, this phenomenon is linked to lower resilience, increased vulnerability to stress, and impaired academic performance (Alligood et al., 2024; Mulawarman et al., 2023). Accordingly, attention to emotion regulation processes is particularly important. Effective emotion regulation enables students to cope more effectively with academic and social challenges, build stronger interpersonal relationships, and manage the stresses of academic life more successfully (Vestad & Tharaldsen, 2022). Gross (1999, 2024) conceptualizes emotion regulation as the process through which individuals attempt to influence the type, intensity, and expression of their emotions. Individuals vary in their use of cognitive and behavioral emotion regulation strategies Gross (1999). Studies have demonstrated that emotion regulation directly affects self-efficacy, stress, and mental health (Boemo et al., 2022). Furthermore, emotions are shaped through person–situation interactions and are guided by individuals' active goals, serving as critical drivers of behavior and decision-making (Lerner et al., 2015).

Accordingly, artificial intelligence, particularly large language models (LLMs) such as GPT-4, offers new and promising tools for psychological support, owing to their ability to process natural language (Hady & Fitria, 2025; Kasneci et al., 2023). The use of artificial intelligence has the potential to enhance the effectiveness of student mental health interventions by improving accessibility, enabling faster decision-making, and supporting personalized approaches, provided that such systems are developed in collaboration with mental health professionals (Akat, 2026). Trained on vast amounts of textual data, these models can engage in conversation, analyze text, answer questions, and generate content (Lerner et al., 2015). In educational settings, AI has also been shown to enhance engagement, enable personalized learning, and help identify individual abilities and creativity (Balabdaoui et al., 2024; Priyanka et al., 2024).

Integrating LLMs into psychotherapy, by improving assessment accuracy, reducing costs, and providing personalized support, has the potential to create a significant transformation in mental health care (Kala et al., 2025; Wu et al., 2024). Given their potential, these technologies can deliver therapeutic interventions through mental health applications or intelligent counseling platforms, addressing barriers related to accessibility and treatment costs (Olawade et al., 2024). Since this study focuses on the effectiveness of LLMs in enhancing emotion regulation and reducing rumination, the theoretical background suggests that such tools may improve students' engagement with psychological interventions. However, the adaptation of these technologies to the specific needs of users within cultural contexts such as Iran remains underexplored. Despite the rapid growth of models like ChatGPT, there remains insufficient research on their application in psychological interventions, especially in non-Western societies (Rathje et al., 2024). At the same time, university students are among the most vulnerable groups, often facing stress, anxiety, and chronic ruminative thinking (Onieva-Zafra et al., 2020). Therefore, using LLMs as an accessible, low-cost, and personalized tool could serve as a viable alternative or complement to traditional therapeutic approaches. The present study sought to investigate the effects of large language models (LLMs) on emotion regulation and rumination among university students. In this study, text-based interaction with the GPT-4 model served as the primary intervention, and the variables were assessed using the Emotion Regulation Questionnaire (ERQ) and the Ruminative Responses Scale (RRS).

In this study, the large language model (LLM) was utilized not merely as an assistive tool within a human-centered intervention but as a quasi-autonomous digital intervention operating with minimal direct human oversight. This conceptual distinction is of particular significance, as quasi-autonomous AI-based interventions raise ethical, safety, and clinical validity considerations that differ fundamentally from those associated with therapist-supportive tools.

Accordingly, the findings of this study should be interpreted within the context of the experimental and exploratory deployment of LLMs as an independent, non-human intervention, rather than as a substitute for or direct adjunct to therapist-led psychological treatments. The main objective of this study was to investigate the effects of a large language model–based intervention on selected psychological indicators among students. Although theoretically important, variables such as distress tolerance and user experience were not measured using standardized instruments in this study; accordingly, any reference to these constructs is purely theoretical. Given the exploratory nature of the study and the instruments employed, the research hypotheses were limited to variables that were directly measured and analyzed. Variables such as *distress tolerance* and *user experience*, which are important for future research, were not systematically measured in this study and were therefore excluded from the final hypotheses.

2. Research Objectives

This study aimed to examine the effectiveness of a large language model (LLM)-based intervention in enhancing emotion regulation and reducing rumination among university students.

Methods and Materials

Study Design

This study employed a quasi-experimental design with pre-test, post-test, and three-month follow-up phases. This study employed a quasi-experimental, controlled design using a convenience sample of students. Allocation to the intervention and control groups was quasi-randomized due to practical constraints; therefore, the study does not meet the criteria for a randomized controlled trial (RCT). The control group received no intervention. While this design allows for preliminary between-group comparisons, it does not adequately control for nonspecific effects, including attention, intervention novelty, participant expectations, and perceived support. Consequently, causal inferences regarding the specific effects or mechanisms of the LLM-based intervention cannot be drawn. The independent variable was the type of intervention (use of a large language model), while the dependent variables included emotion regulation and rumination. Additional factors such as age, gender, field of study, and level of technological familiarity were treated as control variables. In the intervention group, the intervention consisted of an LLM-based program delivered via ChatGPT, whereas the control group received no intervention.

3.1 Sample and Sampling Method

A stratified random sampling method was used to ensure a balanced representation of participants by gender and field of study. During the initial screening phase, 114 of 144 students (79%) were excluded for failing to meet the inclusion criteria or unwillingness to participate, resulting in a final sample of 30 students (21%) who entered the intervention phase. Owing to the voluntary nature of participation, the final sample was likely enriched for students with higher motivation, greater digital literacy, and more favorable attitudes toward AI technologies. Data collection and follow-up procedures were completed for both groups (Figure 1). Given the study objectives, practical constraints, and the need to achieve adequate statistical power (minimum 0.8), the sample size for each group was set at 15 participants. This number was determined based on previous studies in similar domains and was deemed sufficient for conducting the intended statistical analyses, including analysis of covariance (ANCOVA) and repeated-measures ANOVA. Consequently, the intervention group comprised 15 students who received the LLM-based intervention, while the control group consisted of 15 students who received no intervention.

Instruments

Data were collected using the Emotion Regulation Questionnaire (ERQ) and Ruminative Responses Scale (RRS). ERQ comprises two independent subscales: cognitive reappraisal and expressive suppression. In the present study, to reduce analytical complexity given the small sample size, a total ERQ score was used as a global index of emotion regulation. This methodological choice precludes interpretation of the differential contributions of reappraisal and suppression processes. ERQ, developed by Gross & John (2003), assesses emotion regulation strategies through 10 items organized into two subscales: *cognitive reappraisal* (6 items) and *expressive suppression* (4 items). Responses are recorded on a 7-point Likert scale ranging from 1 (*strongly disagree*) to 7 (*strongly agree*). Regarding validity, the reappraisal subscale correlates with positive affect at 0.24 and with negative affect at 0.14, whereas the suppression subscale correlates with positive affect at 0.15 and with negative affect at 0.04 (Balzarotti et al., 2010). Reported Cronbach's alpha coefficients are 0.79 for reappraisal, 0.73 for suppression, and 0.69 for the total scale after three months (Gross, 2015; Gross & John, 2003). This study reported a Cronbach's alpha reliability of 0.70.

The *Ruminative Responses Scale* (RRS), developed by Nolen-Hoeksema & Morrow (1993), consists of 22 items measuring the extent of rumination. Responses are rated on a 4-point Likert scale from 1 (*almost never*) to 4 (*almost always*), yielding total scores from 22 to 88. Scores below 33 indicate low rumination, whereas higher scores indicate greater rumination. The scale comprises three subscales: *distraction*, *brooding*, and *reflection*. Reported Cronbach's alpha values range from 0.88 to 0.92 Nolen-Hoeksema & Morrow (1993), with six-month test-retest reliability at 0.86 (Muris et al., 2005). Its validity was supported by a correlation of 0.56 with the Beck Depression Inventory-II (BDI-II) (Williams & Moulds, 2007). RRS comprises subscales assessing distraction, brooding, and reflection. However, only the total rumination score was included in the statistical analyses of this study. This analytical decision may have obscured subtle yet clinically meaningful differences among distinct forms of rumination. The study reported Cronbach's alpha coefficients of 0.90 for the total scale and between 0.89 and 0.92 for the subscales.

3.3 Procedure

Following initial screening, eligible participants were randomly assigned to either the intervention or control group. The members of the intervention group attended eight weeks of structured sessions delivered via a large language model (ChatGPT), focusing on emotion regulation training and strategies to manage ruminative thinking. The demographic data, tool interaction data (frequency of LLM use and level of cognitive engagement), and dependent variables were measured and collected at three time points. The control group received no intervention during this period. The eight-session intervention protocol for enhancing emotion regulation and reducing rumination was developed based on existing intervention frameworks and published guidelines. The program incorporated evidence-based strategies such as mindfulness exercises, cognitive restructuring, and emotional awareness training. The final structure of this eight-session protocol was specifically designed to reduce maladaptive rumination patterns and enhance emotion regulation skills (Table 1):

Table 1

The structure of the eight-session LLM-based intervention program

Session	Session title	Objectives	Sample prompts used in interaction with the language model
1	Introduction and orientation	Introducing the concepts of emotion regulation and rumination to foster motivation for active participation in the sessions.	1. *Please explain what emotion regulation is and why it is important for mental health.* 2. *How can I recognize my negative thoughts and ruminative thinking?* 3. *Can you give me an example of rumination and its impact on my emotions?*
2	Identifying automatic thoughts	Supporting the participant in recognizing negative and automatic thoughts in various situations	1. *This situation happened to me: [describe situation]. Can you help me identify my negative thoughts?* 2. *Thoughts like [insert negative thought] keep repeating in my mind. Is this thought rational? Why or why not?* 3. *How can I record my negative thoughts more accurately? Please give me an example.*
3	Cognitive restructuring	Teaching strategies to challenge irrational thoughts and replace them with logical, adaptive ones.	1. *This negative thought came to my mind: [insert negative thought]. Can you help me challenge it?* 2. *What rational or alternative thoughts could I have instead of this belief: [insert negative thought]?* 3. *Please give me an example of challenging a negative thought and its replacement.*
4	Emotional awareness and regulation	Enhancing emotional awareness and practicing effective strategies for managing them.	1. *I am feeling [insert emotion]. Can you help me find the reason for it?* 2. *What strategies exist for managing the feeling of [insert emotion]?* 3. *If I am in a stressful situation, what would you suggest to regulate my emotions? Please provide one practical strategy.*
5	Acceptance and mindfulness	Teaching skills for accepting thoughts and feelings, and practicing mindful attention.	1. *Can you give me a simple exercise to increase my mindfulness?* 2. *How can I accept and cope with my unpleasant thoughts or emotions?* 3. *Can you design a 5-minute meditation exercise for me?*
6	Stress management and problem-solving	Strengthening coping skills for stressful situations and teaching problem-solving steps.	1. *I am facing this problem: [describe problem]. Can you help me find a solution?* 2. *What are the steps of problem-solving? Can you apply them to the problem I*

			mentioned? 3. How can I cope with the stress caused by this situation? Please suggest one strategy.
7	Preventing rumination relapse	Identifying triggers for returning to ruminative thinking and designing preventive strategies.	1. *What factors might cause me to return to ruminative thinking?* 2. *Can you help me design a prevention plan for rumination?* 3. *If I notice myself getting caught in repetitive negative thoughts again, what can I do?*
8	Summary and closure	Reviewing the skills learned and developing a plan to continue practicing them in daily life.	—

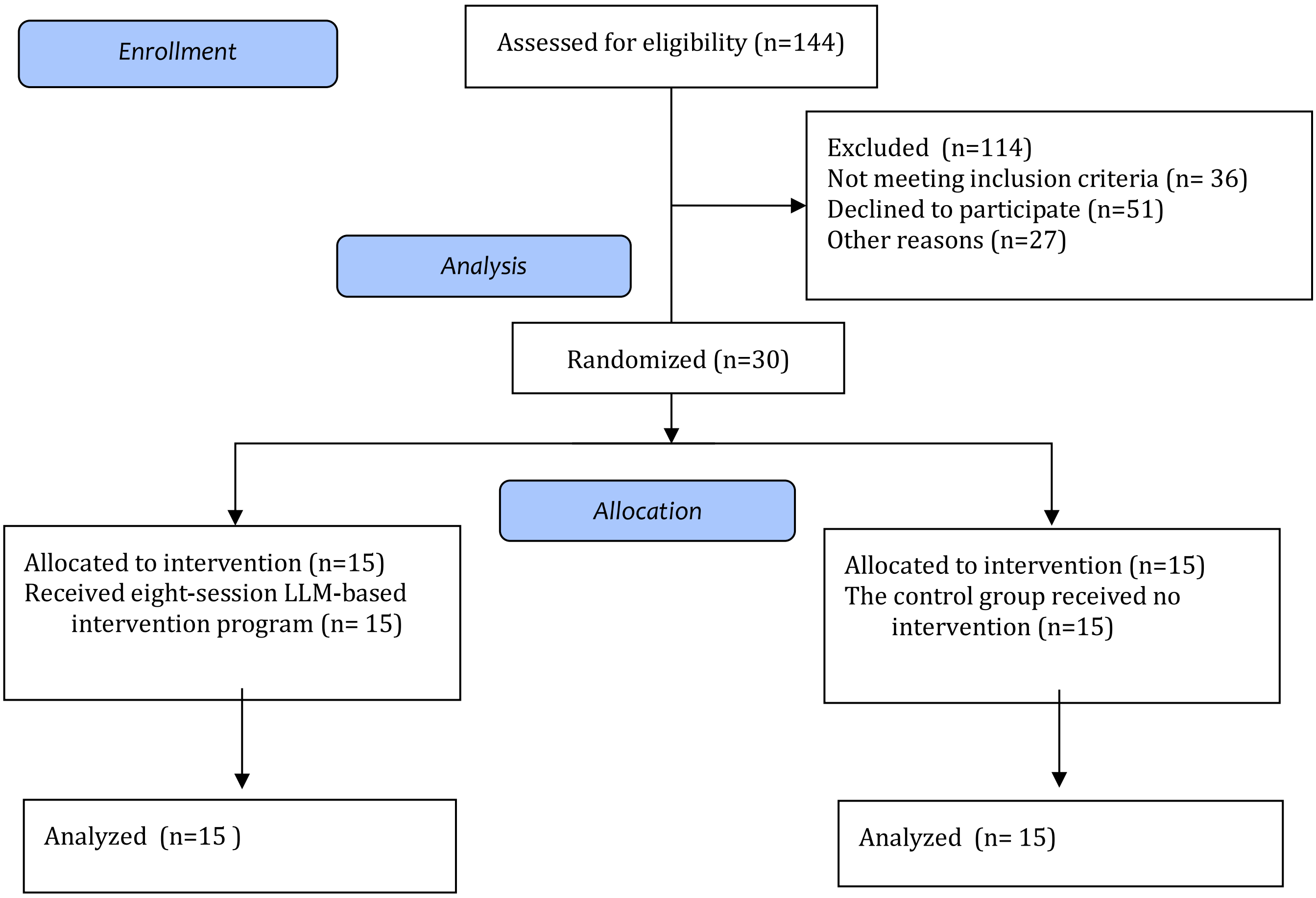

Figure 1

The CONSORT Flow Chart of the study process

Data Analysis

Descriptive statistics, including mean, standard deviation, frequency, percentage, and graphical representations, were employed. To examine both short- and long-term intervention effects, analysis of covariance (ANCOVA) was used to control for pretest variables, and repeated-measures analysis of variance (RM-ANOVA) was conducted to assess the stability of effects at the three-month follow-up. The independent samples t-test and paired samples t-test were applied for intragroup and intergroup comparisons, respectively. Multivariate analysis of variance (MANOVA) was also performed to simultaneously investigate the effects of the intervention on emotion regulation and rumination. For all analyses, effect sizes (Eta Squared) and significance levels were reported.

Ethical Considerations

The protocol for this study was approved by the Research Ethics Committee of Islamic Azad University (https://ethics.research.ac.ir/IR.IAU.TNB.REC.1404.039). Prior to study entry, all participants provided written informed consent and were fully informed about the nature of the language model–based intervention, procedures for data collection and storage, the potential involvement of external data-processing systems, and the safety limitations inherent to AI technologies.

Throughout the study, participants' well-being was actively and periodically monitored. A predefined emergency management protocol was also established, enabling participants to promptly contact a qualified therapist and be referred in cases of significant distress, symptom exacerbation, or urgent need for specialized support.

Despite these safeguards, interactions with the language model were conducted without real-time human monitoring of conversational content, and the system did not perform automated clinical judgment or treatment decision-making. Consequently, the absence of continuous human supervision of interactions and the limited control over data processing in external environments were considered unavoidable ethical and methodological limitations of the study.

All participants provided written informed consent after being fully briefed on the study's aims and were informed of their right to withdraw at any stage. The participants' personal information and results were treated as strictly confidential and used solely for scientific purposes.

Findings and Results

Table 2 presents the demographic characteristics of the participants. As shown, the majority of participants were female students (63.3%), which is unsurprising given the study's voluntary nature and focus on mental health–related topics. Regarding marital status, more than half of the participants were single (56.7%). The distribution of academic disciplines indicates that the highest frequencies were among students in Psychology (36.7%) and Elementary Education (33.3%), which aligns with the research focus on emotion regulation and rumination. In terms of education level, the largest proportion of the participants were bachelor's students (53.3%), a developmental stage in which issues such as academic stress and cognitive-emotional processing are often more salient. This balanced distribution strengthens the validity of the findings by enabling the analysis of intervention effects across diverse subgroups.

Table 2

Demographic distribution of the participants (n = 30)

Variable	Level/Group	Experimental (N=15)	Control (N=15)	Total (N=30)
Gender	Female	9 (60.0)	10 (66.7)	19 (63.3)
	Male	6 (40.0)	5 (33.3)	11 (36.7)
Marital status	Single	8 (53.3)	7 (46.7)	15 (50.0)
	Married	7 (46.7)	8 (53.3)	15 (50.0)
Field of study	Sociology	5 (33.3)	6 (40.0)	11 (36.7)
	Education Sciences	5 (33.3)	4 (26.7)	9 (30.0)
	Accounting	3 (20.0)	4 (26.7)	7 (23.3)
	Physical Education	2 (13.3)	1 (6.7)	3 (10.0)
Academic level	Associate's Degree	3 (20.0)	3 (20.0)	6 (20.0)
	Bachelor's Degree	7 (46.7)	6 (40.0)	13 (43.3)
	Master's Degree	5 (33.3)	6 (40.0)	11 (36.7)

The paired-samples t-test in Table 3 indicated that, in the intervention group, the mean rumination score decreased from 50.73 (SD = 12.45) at pre-test to 35.80 (SD = 9.80) at post-test, reflecting a statistically significant change ($t(14) = 17.39$, $p < .001$). Similarly, the mean emotion regulation score increased from 46.33 (*SD* = 6.51) to 55.20 (*SD* = 5.59), also demonstrating a statistically significant improvement ($t(14) = -16.91$, $p < .001$). In the control group, although changes in both variables were statistically significant, the magnitude of change was substantially smaller, suggesting that these effects were likely due to random variation or external influences rather than the intervention.

Table 3

Comparing the rumination and emotion regulation scores in the pre-test and post-test by group

Group	Variable	Pre-test (Mean ± SD)	Post-test (Mean ± SD)	*t* (df)	*P*-value	Outcome
Intervention	Rumination	50.73 ± 12.45	35.80 ± 9.80	17.39 (14)	< .001	Significant decrease
	Emotion regulation	46.33 ± 6.51	55.20 ± 5.59	−16.91 (14)	< .001	Significant increase
Control	Rumination	58.67 ± 8.92	57.80 ± 8.03	2.48 (14)	.027	A slight significant decrease
	Emotion regulation	45.40 ± 6.52	46.13 ± 6.05	−3.21 (14)	.006	A slight significant increase

Subsequent analyses using analysis of covariance (ANCOVA) and two-stage repeated measures analysis of variance (RM-ANOVA) (Table 4) revealed that the main effects of group and time, as well as the time × group interaction, were statistically significant for both variables. For rumination, the effect of time was very large (η^2 = 0.78), and the time × group interaction also showed a large effect size (η^2 = 0.70). Similarly, for emotion regulation, the effect of time (η^2 = 0.61) and the time × group interaction (η^2 = 0.52) were statistically significant and rated as large in magnitude. These findings indicated that the LLM-based intervention was substantially more effective than the control condition in improving the target variables.

Complementary analyses using repeated measures ANOVA across three time points (pre-test, post-test, and three-month follow-up), as presented in Table 4, demonstrated that changes in both variables over time were statistically significant. For rumination, the effect of time ($F(2, 56) = 39.7$, $p < .001$, $\eta^2 = 0.58$) and the time × group interaction ($F(2, 56) = 16.4$, $p < .001$, $\eta^2 = 0.47$) supported the sustained impact of the intervention up to three months after the completion of the sessions. For emotion regulation, the effect of time (η^2 = 0.49) and the time × group interaction (η^2 = 0.35) were also significant and of substantial magnitude.

Table 4

Results of ANCOVA for post-test scores controlling for pre-test, and repeated measures ANOVA (pre-test, post-test, three-month follow-up) for rumination and emotion regulation

Variable	Source of variation	SS	df	MS	*F*	*p*-value	η^2 (Effect Size)
Rumination	Group	540.30	1	540.30	14.75	.001	—
	Pre-test	680.45	1	680.45	18.57	< .001	—
	Error	1760.80	27	65.21	—	—	—
	Time (pre → post)	—	1	—	96.84	< .001	0.78 (very large)
	Group	—	1	—	20.41	< .001	0.43 (large)
	Time × Group	—	1	—	62.57	< .001	0.70 (very large)
Emotion Regulation	Group	388.70	1	388.70	11.82	.002	—
	Pre-test	745.60	1	745.60	22.68	< .001	—
	Error	1635.30	27	60.57	—	—	—
	Time (pre → post)	—	1	—	43.39	< .001	0.61 (very large)
	Group	—	1	—	5.72	.024	0.17 (medium)
	Time × Group	—	1	—	29.55	< .001	0.52 (large)
Rumination	Time (pre, post, follow-up)	4820.7	2	2410.35	39.7	< .001	0.58 (very large)
	Group	2870.1	1	2870.1	42.5	< .001	0.62 (very large)
	Time × Group	1983.5	2	991.75	16.4	< .001	0.47 (large)
Emotion Regulation	Time (pre, post, follow-up)	1873.2	2	936.6	21.9	< .001	0.49 (large)
	Group	860.4	1	860.4	17.1	< .001	0.41 (large)
	Time × Group	742.8	2	371.4	11.5	< .001	0.35 (medium-to-large)

Overall, the findings demonstrated that the large language model (LLM)-based intervention produced statistically significant and substantial improvements in reducing rumination and enhancing emotion regulation in the intervention group, with these effects persisting at the three-month follow-up.

Discussion and Conclusion

This study examined the impact of interventions based on large language models (LLMs), such as GPT-based chatbots, on emotion regulation and the reduction of rumination among university students. Because the emotion regulation subscales were not analyzed separately, observed changes in overall emotion regulation cannot be attributed to specific processes such as reduced emotional suppression or improved cognitive reappraisal; such interpretations remain speculative and should be treated as hypotheses for future research. The findings demonstrated that these interventions significantly facilitated cognitive restructuring and decreased emotional suppression, aligning with the human-AI interaction theory and cognitive-behavioral approaches. LLMs, by providing interactive responses, assist with cognitive reappraisal and the modification of maladaptive emotion-regulation patterns, creating a safe space for revisiting intrusive thoughts. Overall, these models demonstrate remarkable effectiveness as complementary tools in psychological interventions for enhancing cognitive and emotional processes.

These results are consistent with similar studies conducted in other countries, such as those by Li et al. (2025), Schillings et al. (2024), and Weiss et al. (2024) in Hong Kong, which have shown that digital interventions reduce rumination and stress. However, discrepancies exist regarding the effects of such interventions on depression and anxiety reduction. For instance, Sadeh-Sharvit et al. (2023) reported significant decreases in depressive and anxiety symptoms. In contrast, Weiss et al. and Schillings et al. found these effects to be non-significant, likely due to differences in intervention type, duration, and sample characteristics. Moreover, studies like Liu et al. (2024) emphasized the role of advanced deep learning and transformer models in simulating emotions and improving the quality of psychological interventions.

Other studies have highlighted improvements in mindfulness, self-regulation, and reductions in rumination following digital interventions (Conley et al., 2024). Nonetheless, challenges such as implementation difficulties and user acceptance issues, as noted by Austin et al. (2024) and Wang et al. (2025), underscore the importance of addressing technical and practical considerations. Furthermore, the long-term effects of these interventions require more rigorous investigation, as some studies indicate that reductions in anxiety and depression symptoms may diminish over time (Mehta et al., 2025).

Previous studies have also demonstrated that personalized machine learning models can accurately identify users' psychological states and enable early interventions (Cook et al., 2019; Ghandeharioun et al., 2019). Mobile psychotherapy applications have shown significant efficacy in alleviating depressive symptoms (Fitzpatrick et al., 2017; Inkster et al., 2018).

From a technological perspective, systems based on natural language processing (NLP), deep neural networks (DNNs), and machine learning have been widely employed in clinical data analysis and the diagnosis of mental disorders (Bhamidipaty et al., 2025; Rowshon et al., 2025). These technologies can detect emotions through multimodal analysis (facial expressions, voice, text) and support emotion regulation and adaptive behaviors (Al Maruf et al., 2024; Kusal et al., 2023).

Focusing on an Iranian sample, the present study showed that LLMs can serve as effective collaborators in cognitive-behavioral therapy by reconstructing dysfunctional beliefs and regulating emotions, providing cognitive-emotional support for individuals with chronic rumination or limited access to therapists. It also highlighted the necessity of critical training on their application within psychology curricula and online intervention designs. However, limitations such as a focus on digitally literate students, the intervention's short-term nature, and individual differences in technology engagement were noted. Future studies need to adopt longitudinal designs, expand the range of psychological variables, and develop hybrid human-machine models. Ultimately, the scientific and ethical use of LLMs holds promise as an effective tool for improving emotion regulation, reducing rumination, and enhancing public mental health, particularly in underserved communities.

This study showed that large language models (LLMs), such as GPT-based chatbots, can be valuable tools for improving emotion regulation and reducing rumination in university students. By helping students reframe negative thoughts and manage emotions in healthier ways, LLMs created an interactive space that supported self-reflection and reduced reliance on emotional suppression. These findings suggest that LLMs can be used as supportive resources alongside traditional psychological interventions.

The results are consistent with many international studies showing the benefits of digital interventions for reducing stress and rumination. However, differences remain regarding their effect on depression and anxiety, which may depend on how long the interventions are used, the type of program, and the characteristics of the participants. Importantly, this study also highlighted the need for practical training and careful planning to ensure that LLM-based tools are used effectively in psychology programs and online interventions.

Although the intervention was short-term and limited to digitally literate students, the findings point to significant opportunities for using AI to expand access to mental health support, especially in communities with limited resources. Moving forward, longer-term studies and hybrid human-AI models will be important to ensure sustainable and meaningful improvements in mental health.

Limitations and Suggestions for Future Research

This study has several limitations. The sample consisted of digitally literate university students, which limits the generalizability of the findings to broader populations, particularly those with limited access to or familiarity with technology. The short-term nature of the intervention also prevents conclusions about the sustainability of its effects over time. In addition, individual differences in technology engagement may have influenced outcomes, as some participants may have been more comfortable interacting with AI-based tools than others. Finally, the focus on a limited set of psychological variables did not capture the broader impact of large language model (LLM) interventions on mental health.

Despite the findings, this study has several methodological and ethical limitations that should be considered when interpreting the results. First, the sample was small and drawn from a convenience sample, with participation in the screening phase being voluntary. As a result, the final sample was likely enriched for students with higher motivation, greater digital literacy, and more favorable attitudes toward AI technologies, limiting generalizability. Additionally, participant allocation to intervention and control groups was quasi-randomized, and the control group did not receive an active intervention. The inability to blind participants further constrains causal interpretation.

Second, the study relied primarily on self-report instruments. For constructs such as emotion regulation and rumination, only total scores were analyzed, precluding the examination of subscale-specific effects. Consequently, claims regarding reductions in emotional suppression, facilitation of cognitive reappraisal, or differences among rumination types must be considered speculative and treated as hypotheses rather than definitive findings.

Third, although participants were monitored throughout the study and a clear emergency management protocol was in place, potential negative consequences of AI-based interventions were not systematically assessed using dedicated instruments. Interactions with the language model were conducted without real-time human supervision of conversational content, and the system did not perform automated clinical judgment or treatment decision-making. Similarly, the study could not fully control data processing in external contexts, highlighting unavoidable ethical and methodological limitations.

Taken together, these limitations underscore the exploratory nature of the study and the need for future research with larger samples, active control groups, systematic measurement of subscale-specific outcomes, structured assessment of adverse events, and more rigorous study designs.

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Declaration of Interest

The authors of this article declared no conflict of interest.

Ethical Considerations

The study protocol adhered to the principles outlined in the Declaration of Helsinki, which provides guidelines for ethical research involving human participants.

Ethical considerations in this study were that participation was entirely optional.

Transparency of Data

In accordance with the principles of transparency and open research, we declare that all data and materials used in this study are available upon request.

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Authors' Contributions

All authors equally contribute to this study.

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