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Study on the Negative Impact of AI Social Compensation on Depression Tendencies: The More You Use It, The Lonelier You Get

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Abstract

This study examined the negative impact of AI social compensation on depressive tendencies among college students and its underlying mechanisms. Based on a survey of 328 students, the results indicate that AI social compensation is a significant predictor of depressive tendencies, with loneliness playing a partial mediating role. Furthermore, social presence positively moderates the effect of AI-mediated social compensation on loneliness. This study reveals that, in natural, non-interventional settings, overreliance on AI for social compensation may trap individuals in a "the more you use it, the lonelier you get" dilemma, providing empirical evidence for mental health interventions and risk prevention in the context of AI use.

Keywords

AI social compensation; depressive tendencies; loneliness; social presence.

1. Introduction

With the rapid iteration of artificial intelligence technology and breakthroughs in generative models, conversational AI has evolved from a tool-based assistant to an anthropomorphized social entity. Research shows that AI has become a highly anthropomorphic system integrating deep learning, affective computing, and large language models, and its ability to simulate empathic responses of human experts has gained strong empirical support [1]. Among college students, intelligent agents capable of accurately identifying psychological states and providing empathetic feedback have deeply integrated into daily life, effectively meeting the core need for companionship, and are often used for emotional regulation and communication [2].Compensatory internet use theory holds that people turn to online interaction to make up for gaps in their offline social lives — a kind of self-regulation against everyday stress. Drawing on this stress-avoidance and compensation logic together with the displacement hypothesis [3,4], this study introduces the concept of AI social compensation for the first time: when people run into obstacles in real-life social interaction, they turn to AI with human-like qualities for communicative support, using it as a substitute or supplement for genuine relationships to meet emotional needs. This shifts the target of compensation from online communities to responsive intelligent agents, and the behavior itself from passive browsing to active, simulated social engagement — making AI social compensation, in effect, a modern extension of CIU theory in the AI era. Though it offers short-term relief, such virtual interaction can crowd out real social engagement and erode relationship quality over time; this dual compensatory-and-corrosive effect points to psychological risks that may build up gradually [5].

Critically, loneliness matters here in two ways. First, it is the main force pushing people toward AI social compensation. Second, it works as the bridge that connects social experience to depressive tendencies. Social isolation and a strong sensitivity to perceived threat give rise to loneliness, and this in turn creates a deep wish to rebuild social ties [6]. College students going

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through hard transitions often find comfort in AI, since its low risk and predictable nature feels safer than real relationships. Those who feel lonely tend to notice AI's social presence quite easily and take real comfort from it, though what they are getting is closer to a one sided, user centered pseudo friendship than genuine connection. Leaning on these seemingly caring, algorithm run environments for too long tends to erode real social skills and the ability to work through conflict. This fits the displacement hypothesis, where AI dependence pushes out real relationships, deepens loneliness [7], and predicts later depressive tendencies [8]. Escaping real interaction through AI often worsens withdrawal, trapping people in shallow bonds and lasting loneliness [5].

Persistent loneliness ultimately paves the way for depressive tendencies, a process in which AI's social presence serves a complex moderating role. Prevalent subthreshold depression among college students, though subclinical, heavily impairs emotional regulation and social functioning. Crucially, while structured AI interventions effectively relieve depression, natural usage scenarios paint a different picture: high-frequency use of companion AI and the resulting emotional dependence are tied to heightened depression risks [9]. Here, social presence prompts users to perceive AI as a sentient, co-present entity rather than a machine, boosting interactive naturalness and anthropomorphic trust [10]. However, when strong digital companionship is coupled with a lack of meaningful real-life feedback, the psychological gap exacerbates loneliness and further reinforces depressive tendencies [11]. Although previous literature links AI usage to mental health, systematic exploration of the underlying mechanisms remains limited. To bridge this gap, our study constructs an empirical model using AI social compensation as the independent variable, depressive tendency as the dependent variable, loneliness as the mediating variable, and social presence as the moderating variable. This framework elucidates why more frequent use of AI tends to exacerbate feelings of loneliness. Ultimately, these insights not only deepen the theoretical understanding of human-computer interaction but also provide an empirical basis for monitoring students' mental health, developing clinical interventions, and designing more human-centered AI technologies.

2. Theoretical Analysis and Research Hypotheses

Compensatory Internet Use Theory The theory of compensatory internet use posits that college students often turn to virtual environments to relieve stress and regulate emotional distress; this escapist behavior is, in essence, a more telling indicator of psychological risk than the mere accumulation of usage time [3]. If AI-driven compensatory interactions fail to provide substantial social support, they may inadvertently trigger depressive symptoms. It follows, then, that H1: AI social compensation is a significant positive predictor of depressive tendencies.

Mechanistically speaking, loneliness is a key precursor to depression, leading to latent hypervigilance, biased social cognition, and heightened rumination [6]. Driven by these dynamics, H2 posits that loneliness is a significant positive predictor of depressive tendencies. Moreover, the interplay between AI social compensation and loneliness is inherently bidirectional: whenever there is a gap between real-life support networks and idealized interactions with AI, overreliance on non-human relationships leads to social maladjustment [7]. This "rebound" effect of loneliness essentially plays a central mediating role. It follows that H3: Loneliness mediates the relationship between AI social compensation and depressive tendencies.

Furthermore, a sense of social presence plays a moderating role. A higher sense of social presence enhances emotional attachment to and anthropomorphic perceptions of AI, thereby deepening the tendency to substitute real-world social interactions with virtual ones [10]. This engagement amplifies the impact of compensatory behaviors on loneliness, which in turn exacerbates feelings of isolation. Thus, we propose H4: Social presence moderates the effect of

AI social compensation on loneliness; specifically, higher social presence strengthens this positive impact. Collectively, this study constructs a moderated mediation model. We propose H5: Social presence moderates the first half of the mediating pathway; specifically, higher social presence increases the indirect effect of AI social compensation on depressive tendencies through loneliness.

3. Method

This study employed a cross-sectional research design and collected data through a questionnaire survey. The study participants were college students recruited online using convenience sampling and snowball sampling; a total of 328 valid questionnaires were obtained.

The study employed well-established scales for measurement: the AI Attachment Scale (15 items, 5-point Likert) was used to measure AI social compensation [12]; the short-form UCLA Loneliness Scale (ULS-6, 6 items, 4-point) was used to measure loneliness [13]; the PHQ-9 (9 items, 4-point) was used to assess depressive tendencies [14]; and the Robot Social Presence Scale (17 items, 7-point) was used to measure social presence [15,]. Higher scores on each scale indicate higher levels of the corresponding variable.

To eliminate the influence of different dimensions, all core variables were standardized using Z-scores before correlation and regression analyses. Hierarchical regression and the Bootstrap method were used to test mediating and moderating effects.

4. Research Results

4.1. Common Method Bias

To assess potential common method bias (CMB) inherent in cross-sectional self-reports, Harman's single-factor test was performed. Exploratory factor analysis (without rotation) revealed that the first principal factor accounted for 34.59% of the total variance. This value remains below the 40% threshold, indicating that CMB does not pose a significant concern and the data are suitable for further analysis.

4.2. Correlation Analysis

The Pearson correlation coefficient matrices for each study variable are shown in Table 1. AI social compensation was significantly positively correlated with loneliness ($r = 0.353$, $p <.001$), with depressive tendencies ($r = 0.426$, $p <.001$), and with social presence ($r = 0.405$, $p <.001$). Loneliness was highly positively correlated with depressive tendencies ($r = 0.634$, $p <.001$), providing preliminary evidence for the existence of a mediating effect. Social presence was also significantly positively correlated with loneliness ($r = 0.292$, $p <.001$) and depressive tendencies ($r = 0.227$, $p <.001$).

4.3. Regression Analysis

To validate study hypotheses H1 and H2 and to lay the foundation for the mediating effect test, this study constructed a three-level regression model using gender, grade, major, and average daily usage duration as control variables. The results are shown in Table 2.

In Models 1 and 2, AI social compensation significantly and positively predicted both depressive tendencies($\beta = 2.644$, $t = 8.271$, $p <.001$, $R^2 = 0.187$), and loneliness ($\beta = 0.285$, $t = 6.545$, $p <.001$, $R^2 = 0.140$), supporting hypothesis H1 and confirming the a path of the mediating pathway. In Model 3, with loneliness added as a predictor, it showed a significant positive effect on depressive tendencies ($\beta = 4.160$, $t = 12.334$, $p <.001$), supporting H2. Notably, the regression coefficient of AI social compensation on depressive tendencies decreased from

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2.644 to 1.458 while remaining significant, and the total explained variance R^2 increased to 0.448, suggesting a partial mediating effect of loneliness between the two.

Table 1. Descriptive statistics of each study variable and Pearson correlation coefficient matrix (N = 328)

Variables	M	SD	1	2	3	4	5	6	7
1. AI social compensation	3.21	0.57	—						
2. Loneliness	2.20	0.48	0.353 ***	—					
3. Tendency towards depression	9.85	3.63	0.426 ***	0.634 ***	—				
4. Social presence	4.59	1.00	0.405 ***	0.292 ***	0.227 ***	—			
5. Gender	1.61	0.49	-0.061	-0.086	-0.057	-0.067	—		
6. Grade	2.56	1.23	0.059	0.093	0.068	-0.025	0.024	—	
7. Major	2.84	1.74	-0.069	-0.082	-0.077	0.012	0.034	-0.060	—

Note: * p <.05, ** p <.01, *** p <.001 (two-tailed test). Gender: 1 = male, 2 = female; Grade: 1 = Freshman to 5 = graduate; Major: 1 = Science and Engineering to 7 = Other. AI Social Compensation, Loneliness, Social Presence Report Likert average score; Depression tendency is a PHQ-9 total score.

Table 2. Results of Hierarchical Regression Analysis (N = 328)

Predictor variables	Model 1DV: Tendency towards depressionβ (t)	Model 2DV: Lonelinessβ (t)	Model 3DV: Tendency towards depressionβ (t)
Control variables			
Gender	-0.227 (-0.609)	-0.064 (-1.248)	0.037 (0.120)
Grade	0.123 (0.826)	0.028 (1.401)	0.005 (0.038)
Major	-0.091 (-0.862)	-0.014 (-0.944)	-0.034 (-0.395)
Average daily usage duration	0.131 (0.523)	0.038 (1.114)	-0.027 (-0.131)
Main variable			
AI social compensation	2.644*** (8.271)	0.285*** (6.545)	1.458*** (5.193)
Feelings of loneliness	—	—	4.160*** (12.334)
Constant	1.402 (0.996)	1.275*** (6.643)	-3.902** (-3.150)
Sample size	328	328	328
R^2	0.187	0.140	0.448
Adjust R^2	0.174	0.127	0.438
F value	F (5322) = 14.822 ***	F (5322) = 10.525 ***	F (6321) = 43.502 ***

Note: β is the non-standardized regression coefficient, with t values in parentheses; All models are included in the intercept term. * p <.05, ** p <.01, *** p <.001.

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4.4. Mediating effect test

To test hypothesis H3, this study used the Bootstrap method recommended by Hayes (sample size B = 5,000, 95% bias-corrected confidence interval) to estimate each effect path, and the results are shown in Table 3.

The indirect effect of AI social compensation on depressive tendencies through loneliness was 1.186 (95% CI = [0.799, 1.604], SE = 0.204), which was significant as the interval excluded zero. Specifically, the effect of AI social compensation on loneliness was 0.285 (95% CI = [0.199, 0.371]), and the effect of loneliness on depressive tendencies was 4.160 (95% CI = [3.497, 4.824]), both reaching significance. The overall effect was 2.644 (95% CI = [2.015, 3.273]), while the direct effect remained significant at 1.458 (95% CI = [0.906, 2.010]), confirming that loneliness plays a partial mediating role. This indirect path accounted for 44.8% (1.186/2.644) of the total effect, indicating that nearly half of the impact of AI social compensation on college students' depressive tendencies is transmitted through increased loneliness, thereby supporting H3.

Table 3. Test for the mediating effect of loneliness (Bootstrap method, N = 328, B = 5,000)

Pathways	Symbol	Effect value	SE	95% CI	z/t values	p value	Conclusion
AI social compensation → Loneliness → Depressive tendencies	a×b	1.186	0.204	[0.799, 1.604]	5.812	< .001	Partial mediators
AI social compensation → Loneliness (Pathway a)	a	0.285	0.044	[0.199, 0.371]	6.545	< .001	—
Loneliness → tendency to depression (Path b)	b	4.160	0.337	[3.497, 4.824]	12.334	< .001	—
AI social compensation → Depressive tendencies (direct effect c')	c'	1.458	0.281	[0.906, 2.010]	5.193	< .001	—
AI social compensation → Depressive tendencies (total effect c)	c	2.644	0.320	[2.015, 3.273]	8.271	< .001	—

Note: Bootstrap 95% bias corrected confidence interval (BC CI); A CI without 0 indicates a significant effect. Indirect effect mediating ratio = 1.186/2.644 = 44.8%.

4.5. Moderating effect test

To test hypotheses H4 and H5, this study used stratified regression (H4) and Bootstrap regulatory mediation analysis (H5), respectively.

4.5.1. Moderating effects of Social Presence (H4)

With loneliness as the outcome variable and gender, grade, major, and average daily usage duration as control variables, a three-step hierarchical regression was used to test the moderating effect of social presence on the "AI social compensation → loneliness "pathway. The results are shown in Table 4.

In Model 1, AI social compensation significantly predicted loneliness ($\beta = 0.285$, $t = 6.545$, $p < .001$, $R^2 = 0.140$). Adding social presence in Model 2 showed a significant main effect ($\beta = 0.088$, $t = 3.280$, $p = .001$) and increased variance ($\Delta R^2 = 0.028$, $\Delta F = 10.757$, $p = .001$). Model 3's interaction term was significant ($\beta = 0.170$, $t = 4.909$, $p < .001$, $\Delta R^2 = 0.058$, $\Delta F = 24.099$, $p < .001$), confirming social presence positively moderates the "AI social compensation → loneliness" path. Thus, the effect is stronger for those with higher social presence, supporting H4.

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Table 4. Hierarchical regression results of Social presence moderating Effects (DV: loneliness, N = 328)

Predictor variables	Model 1β (t)	Model 2β (t)	Model 3β (t)
Control variables			
Gender	-0.064 (-1.248)	-0.056 (-1.115)	-0.045 (-0.935)
Grade	0.028 (1.401)	0.032 (1.585)	0.030 (1.577)
Major	-0.014 (-0.944)	-0.016 (-1.095)	-0.018 (-1.288)
Average daily usage duration	0.038 (1.114)	0.039 (1.160)	0.021 (0.627)
Main variable			
AI social compensation	0.285*** (6.545)	0.223*** (4.738)	0.213*** (4.682)
Social presence	—	0.088** (3.280)	0.094*** (3.606)
Interaction terms			
AI social compensation × Social Presence	—	—	0.170*** (4.909)
Constant	2.192*** (17.119)	2.175*** (17.227)	2.163*** (17.738)
Sample size	328	328	328
R^2	0.140	0.168	0.227
Adjust R^2	0.127	0.153	0.210
F value	F (5322) = 10.525 * * *	F (6321) = 10.829 * * *	F (7320) = 13.393 * * *
Δ R squared	0.140	0.028	0.058
Δ F	F (5322) = 10.525 * * *	F (1321) = 10.757 * *	F (1320) = 24.099 * * *

Note: t values are in parentheses; All consecutive variables have been mean centered. * p <.05, ** p <.01, *** p <.001. ΔR^2 is the increment of R^2 for the new variable added at each step.

4.5.2. Moderated mediating effect (H5)

To test the hypothesis H5, this study used the Bootstrap method (B = 5,000, 95% CI percentile) to estimate different levels of social presence (high: +1SD; mean; The conditional indirect effect of AI social compensation on depressive tendencies through loneliness at low: −1SD, results shown in Table 5.

The results showed that when social presence was at a high level (+1SD), the indirect effect was 1.591 (95% CI = [0.927, 2.231]), with no confidence interval of 0, and the effect was significant; At the mean level, the indirect effect was 0.885 (95% CI = [0.454, 1.329]), equally significant; At the low level (−1SD), the indirect effect was 0.178 (95% CI = [-0.227, 0.595]), with a confidence interval containing 0, and the effect was not significant. This result suggests that when an individual's social presence perception of AI is low, AI social compensation does not significantly affect their depressive tendencies through loneliness; This indirect effect gradually increases and reaches a significant level as the sense of social presence grows.

The monotonically increasing trend of the above conditional indirect effect with the level of social presence is in line with the theoretical expectation of Moderated Mediation, supporting hypothesis H5: Social presence significantly moderates the first half of the mediating pathway of "AI social compensation → loneliness → depressive tendency ", that is, the higher the social presence, the stronger the indirect effect of AI social compensation on depressive tendency through loneliness.

Table 5. Test of moderated mediating effects: Conditional Indirect effects at different levels of social presence (Bootstrap, N = 328, B = 5,000)

Level of social presence	Level values	Indirect effects	Boot SE	Boot 95% CI	Significance
Low levels (−1SD)	-0.999	0.178	0.207	[-0.227, 0.595]	Not significant
Mean level	0.000	0.885	0.222	[0.454, 1.329]	Significant
High level (+1SD)	+0.999	1.591	0.329	[0.927, 2.231]	Significant

Note: Use the percentile Bootstrap method; BootLLCI and BootULCI are the lower and upper limits of the Bootstrap 95% confidence interval, respectively; A CI without 0 indicates that the effect is significant at that level.

5. Conclusion

This study, which focused on college students, examined a moderating-mediation model of the effects of AI social compensation on depressive tendencies. The results indicate that AI social compensation significantly and positively predicts depressive tendencies, with loneliness accounting for 44.8% of the partial mediating effect, while a sense of social presence positively moderates the first half of the mediating path. When using artificial intelligence for social compensation, college students place greater emphasis on emotional fulfillment, which corroborates the mediating role of loneliness. No significant differences were found across demographic variables such as gender and academic year, indicating that this influence pathway is universal among college students. Its core driving force is the individual's motivation for social compensation, which is consistent with the theory of compensatory internet use (Kardefelt-Winther, (2014).

These findings extend the theory of compensatory internet use to the field of artificial intelligence and are consistent with previous research by Franco-O'Byrne et al. (2023), Cacioppo et al. (2010), and Lai et al. (2025). Regarding social presence, this study builds upon the foundation laid by Weng et al. and Deng and Yan by revealing a distinct tipping point: at lower intensities, the effects are negligible, but once a certain threshold is exceeded, the negative impacts of social compensation through artificial intelligence intensify sharply. This nonlinear dynamic effectively reconciles the conflicting findings that have been scattered throughout the existing literature. Unlike the positive interventions documented by Fitzpatrick et al., our study focuses exclusively on natural usage contexts—in which individuals' avoidance motivations are more likely to trigger adverse psychological consequences. Looking ahead, AI architectures must strike a careful balance between emotional support and social presence; they need to both alleviate users' psychological distress and actively guide them toward face-to-face interpersonal interactions to safeguard their long-term mental health.

This study has certain limitations. First, because it employs a cross-sectional design, it is difficult to establish causal relationships among the variables. Second, the sample is limited to college students, which restricts the generalizability of the findings. Future research should explore causal mechanisms and expand the study to include different populations.

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