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The Moderating Role of Generative AI Conversations in the Relationship Between Perceived Social Support and Quality of Life in Young Adults

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Abstract

This study examines the moderating role of generative artificial intelligence conversations in the relationship between perceived social support and quality of life among 252 young adults (18-30 years). Results indicate that generative AI usage significantly moderates this relationship, with distinct effects depending on the level of dependency. In individuals with low dependency, social support remains the primary predictor of quality of life; however, in those with high dependency, this relationship is substantially attenuated. Analysis reveals that the type of usage significantly influences this effect: emotional and recreational use diminishes the benefits of social support, while informational and professional use does not show this impact. The explanatory mechanism identified shows that emotional use contributes to the development of AI dependency, thereby reducing the ability to leverage traditional social support. These findings emphasize the importance of balanced use of conversational technologies to maintain the benefits of authentic interpersonal relationships.

Keywords: generative artificial intelligence; social support; quality of life; technological dependency

1. Introduction

In the contemporary digital era, traditional social interactions are increasingly being supplemented or even replaced by technologically mediated interactions. Recently, generative artificial intelligence systems have become accessible conversational partners for millions of users. These systems offer not only information but also a form of interaction that mimics human conversations, demonstrating sophisticated capabilities for natural language processing and contextual response (Hancock et al., 2020; OECD, 2021). This mimicry can apparently diminish the need for social support, a fundamental factor for psychological well-being and quality of life (Cohen & Wills, 1985). Numerous studies have demonstrated the direct link between the perception of social support and quality of life indicators, including in young adults (Taylor et al., 2011). However, the way in which emerging technologies, especially conversational AI, influence this relationship remains insufficiently explored.

Recent literature suggests that young people can develop emotional attachments to conversational technologies (Turkle, 2012; Skjuve, 2021), and these systems can provide a certain type of perceived social support (Ta et al., 2020). Empirical studies have shown that interactions with conversational agents can generate social and emotional responses similar to those in human interactions (Nass & Moon, 2000; Mou & Xu, 2017). Artificial agents, including conversational chatbots, can constitute an important source of social support for users, with significant implications for their well-being and quality of life. Although most studies have focused on the role of these technologies in specifically stressful situations or in medical contexts, Ta et al. (2020) highlight the importance of analysing the social support provided by artificial agents in everyday interactions. According to these authors, companion chatbots offer multiple forms of social support, predominantly: companionship support (reducing feelings of loneliness through 24/7 accessibility

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and simulating human communication), emotional support (creating a „safe space" for self-disclosure without fear of being judged), informational support (offering useful advice and information), and appraisal support (facilitating self-reflection and self-evaluation). Interactions with chatbots can provide a level of trust and comfort that encourages self-disclosure, an aspect that can be particularly valuable for young adults who are frequently more reluctant to discuss certain topics with other people due to fears related to social judgment. This dimension of interaction with generative AI may explain the differentiated effects we have identified depending on the type of use and level of dependency.

The conclusions of these studies strengthen the premise of our research that artificial agents, including conversational chatbots, can represent a significant source of social support in everyday life, with potentially transformative implications for the psychological well-being of young adults, thus complementing the traditional social support offered by human interactions. However, although chatbots are perceived as accepting, available, and capable of empathically satisfying users' communication needs, these sources of support can also have a „dark side" that may diminish quality of life. Recent research shows that excessive dependency on AI interactions can lead to social isolation (Eling, 2025, in press), atrophy of interpersonal communication skills, and a distorted perception of authentic relationships (Boyd & Markowitz, 2025, in press). Additionally, studies have highlighted that frequent interactions with chatbots can create unrealistic expectations regarding human communication, as generative AI is programmed to provide optimized responses, lacking the inconsistencies and limitations characteristic of interpersonal communication (Naik et al., 2025, in press). There are voices that warn that AI companions rather reproduce than sustainably reduce the dynamics of loneliness, and loneliness simply becomes „digitized loneliness" (Jacobs, 2024; Lemay et al., 2019).

The present study aims to investigate the moderating role of conversations with generative AI in the relationship between perceived social support and quality of life in young adults. Unlike previous research that has predominantly focused on the direct effects of interactions with AI, our approach examines how these interactions can modify the well-established relationship between traditional social support and the perception of quality of life. This perspective offers a more nuanced understanding of the impact of conversational technologies on young adults, in a period when identity development and establishing significant social relationships represent fundamental processes. The original contribution consists of examining the differentiated effects of interactions with generative AI according to the type of use and level of dependency, thus offering a more nuanced perspective on the conditions in which these technologies can augment or, conversely, diminish the benefits of traditional social support on quality of life. The results can guide both psychological interventions and the development of more responsible AI systems that maximize potential benefits for the well-being of young users while minimizing associated risks.

2. Objective and Hypotheses

2.1. Objectives

1. Evaluating the relationship between perceived social support and quality of life in young adults.
2. Investigating the potential mediating or moderating role of generative AI dependency in this relationship.
3. Exploring differences based on the intensity of generative AI usage and the purpose of interactions.

2.2. Hypotheses

1. There is a significant positive relationship between perceived social support and quality of life in young adults.
2. Generative AI dependency moderates the relationship between social support and quality of life, such that:

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   a. In individuals with low AI dependency, social support remains the primary predictor of quality of life.
   b. At high levels of AI dependency, the relationship between social support and quality of life is attenuated.
3. The type of interaction with generative AI (informational vs. emotional) influences the nature of the moderating effect.

3. Method

3.1. Participants

The study included 252 participants aged between 18 and 30 years, recruited through stratified sampling from academic and professional environments. 139 were female (55.1%). Inclusion criteria were familiarity with generative AI systems and using them at least once a week in the past 3 months.

3.2. Instruments

1. ***Perceived Social Support Scale*** (PSSS) (Zimet et al., 1988). A 12-item instrument that measures the perception of support from family, friends, and significant others, with scores from 1 to 7 on a Likert scale. Psychometric properties include Cronbach's α = .91 and construct validity demonstrated in numerous studies.
2. ***WHOQOL-BREF (WHO, 1998).*** Standardized instrument for assessing quality of life, with 26 items covering physical, psychological, social, and environmental domains. Scores range between 1 and 5, with Cronbach's α = .88 and solid concurrent validity.
3. ***Generative AI Dependency Scale (GADS)*** (Goh, 2025). A recent scale with 11 items that measures psychological dependency on interactions with generative AI. The scale includes subscales for Cognitive Preoccupation (prominence and compulsive use, 3 items e.g., „My decisions are often influenced by generative AI"), Negative Consequences (4 items, e.g., „I feel less confidence in my abilities without generative AI"), and Withdrawal (4 items, e.g., „I experience restlessness if I am unable to use generative AI"). Items are rated on a Likert scale from 1-strongly disagree to 5-strongly agree. Preliminary psychometric properties indicate Cronbach's α = .93.
4. ***Demographic and AI Usage Questionnaire.*** Collects information about age, gender, educational level, frequency of generative AI usage, main purpose of use (informational, emotional, recreational, professional, evaluated on a scale from 1 to 7), and platforms used.

4. Results

4.1. Descriptive Statistics

Descriptive analysis of data by gender reveals significant differences in the perception of social support and patterns of generative artificial intelligence usage. Women report significantly higher levels of perceived social support (M = 5.61, SD = 0.98) compared to men (M = 5.19, SD = 1.17, $p < .01$), with the difference being particularly pronounced for support from friends ($p < .01$) and life partner ($p < .05$).

Regarding quality of life, no significant differences were recorded between genders, suggesting that the perception of general well-being does not vary substantially by gender among young generative AI users.

Concerning generative AI dependency, men show significantly higher scores only in the withdrawal dimension (M = 2.72, SD = 1.18) compared to women (M = 2.48, SD = 1.10, $p < .05$). No significant differences were observed in the other dimensions of dependency.

An interesting aspect is observed in the purpose of generative AI usage, with women reporting significantly more intense use for emotional purposes (M = 3.82, SD = 1.73) compared to men (M = 3.15, SD = 1.67, $p < .01$), while men tend to use AI for recreational purposes (M = 4.87, SD = 1.45) more frequently than women (M = 4.53, SD = 1.58, $p < .05$). For informational and professional purposes, no significant differences were recorded.

Table 1. MSPSS Means and Standard Deviation by gender.

Scale	Men—M (SD) N=113	Women—M (SD) N=139	p
PSSS—Significant other	5.34 (1.27)	5.78 (1.15)	.003*
PSSS—Family	5.21 (1.41)	5.47 (1.33)	.087
PSSS—Friends	5.03 (1.32)	5.58 (1.09)	.001**
PSSS—Total	5.19 (1.17)	5.61 (0.98)	.002**
QOL—Physical	3.87 (0.68)	3.76 (0.72)	.165
QOL—Psychological	3.62 (0.75)	3.47 (0.81)	.097
QOL—Social	3.65 (0.79)	3.72 (0.84)	.464
QOL—Environment	3.74 (0.63)	3.71 (0.68)	.691
GAID—Cognitive	2.86 (1.15)	2.67 (1.09)	.123
GAID—Negative Consequences	2.54 (1.12)	2.43 (1.07)	.366
GAID—Withdrawal	2.72 (1.18)	2.48 (1.10)	.049*
Informational Purpose	5.87 (1.12)	5.73 (1.18)	.290
Emotional Purpose	3.15 (1.67)	3.82 (1.73)	.001**
Recreational Purpose	4.87 (1.45)	4.53 (1.58)	.047*
Professional Purpose	5.63 (1.32)	5.48 (1.41)	.339

*p < .05, **p < .01.

4.2. Testing the Hypotheses

H1: *The Relationship Between Perceived Social Support and Quality of Life*

Results indicate significant positive correlations between perceived social support and all domains of quality of life, supporting the first part of our hypothesis. Correlations are weak to moderate ($r = .25$—.58), with the strongest associations observed between total social support and the social domain of quality of life ($r = .58$, $p < .001$).

Table 2. Correlations between Perceived Social Support and Quality of Life.

Variables	QOL-Physical	QOL-Psychological	QOL-Social	QOL-Environmental
PSSS-Total	.31***	.47***	.58***	.35***
PSSS-Significant Others	.25***	.39***	.51***	.30***
PSSS-Family	.27***	.42***	.44***	.32***
PSSS-Friends	.29***	.43***	.56***	.31***

*Note: ***p < .001.

Regression analysis confirms that perceived social support is a significant predictor of quality of life across all four domains, even after controlling for demographic variables. Its contribution is substantial, explaining between 9% and 32% of the variance in quality of life.

The strongest effect is observed for the social domain of quality of life ($\beta = .57$, $\Delta R^2 = .32$, $p < .001$), followed by the psychological domain ($\beta = .46$, $\Delta R^2 = .21$, $p < .001$). Although the effect is more modest for the physical and environmental domains, social support remains a significant predictor for these aspects of quality of life as well.

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Table 3. Results of hierarchical regression for Predicting Quality of Life.

Predictor Variables	QOL-Physical	QOL-Psychological	QOL-Social	QOL-Environmental
Step 1. Demographic Variables				
Age	.07	.09	.04	.12*
Gender (0=M, 1=F)	-.08	-.10	.06	-.02
Educational Level	.14*	.16*	.10	.20**
R^2	.03	.04	.01	.05*
Step 2. Social Support				
PSSS-Total	.30***	.46***	.57***	.33***
ΔR^2	.09***	.21***	.32***	.11***
Total R^2	.12***	.25***	.33***	.16***

*Note: Values in the table represent standardized beta coefficients. *p < .05, **p < .01, ***p < .001.

H2: *The Moderating Effect of Generative AI Dependency*

To test the moderation hypothesis, we conducted a hierarchical regression analysis with interaction, examining whether the intensity of the relationship between perceived social support and different domains of quality of life varies according to the level of generative AI dependency.

Table 4. Results of moderation analysis for the effect of AI Dependency.

Predictors	QOL-Physical β (SE)	QOL-Psychological β (SE)	QOL-Social β (SE)	QOL-Environmental β (SE)
Step 1				
PSSS-Total	.30*** (.05)	.45*** (.04)	.56*** (.04)	.34*** (.05)
GAID-Total	-.11* (.05)	-.14** (.05)	-.08 (.04)	-.16** (.05)
R^2	.15***	.27***	.34***	.18***
Step 2				
PSSS-Total	.31*** (.05)	.46*** (.04)	.57*** (.04)	.35*** (.05)
GAID-Total	-.12* (.05)	-.15** (.05)	-.09* (.04)	-.17** (.05)
PSSS × GAID	-.17** (.05)	-.19*** (.04)	-.15** (.04)	-.12* (.05)
ΔR^2	.03**	.04***	.02**	.01*
Total R^2	.18***	.31***	.36***	.19***

*Note: Values represent standardized beta coefficients with standard errors in parentheses. *p < .05, **p < .01, ***p < .001.

The analysis reveals a significant interaction effect between perceived social support and AI dependency for all domains of quality of life (coefficients between $\beta = -.12$ and $\beta = -.19$, $p < .05$). To interpret this effect, we calculated the conditional effects at three levels of AI dependency (Table 5).

Table 5. Conditional Effects of Social Support on Quality of Life at different levels of AI Dependency.

AI Dependency Level	QOL-Physical (95% CI)	QOL-Psychological (95% CI)	QOL-Social (95% CI)	QOL-Environmental (95% CI)
Low (-1SD)	.47*** (.35, .59)	.64*** (.53, .75)	.71*** (.61, .81)	.46*** (.35, .57)
Medium (M)	.31*** (.23, .39)	.46*** (.38, .54)	.57*** (.50, .64)	.35*** (.27, .43)
High (+1SD)	.15* (.03, .27)	.28*** (.17, .39)	.43*** (.31, .55)	.24*** (.12, .36)

*Note: Values represent unstandardized regression coefficients with 95% confidence intervals in parentheses. *p < .05, **p < .001.

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The results confirm both components of hypothesis 2:

1. At low levels of AI dependency, the relationship between social support and quality of life is strong (coefficients between .46 and .71).
2. At high levels of AI dependency, the relationship is significantly attenuated (coefficients between .15 and .43).

The attenuating effect is most pronounced for the physical and psychological domains, suggesting that high AI dependency may particularly interfere with the benefits of social support on these aspects of quality of life. The social domain, although affected by moderation, appears to be the most resilient, indicating that social support remains a relatively strong predictor of social quality of life even in the presence of AI dependency.

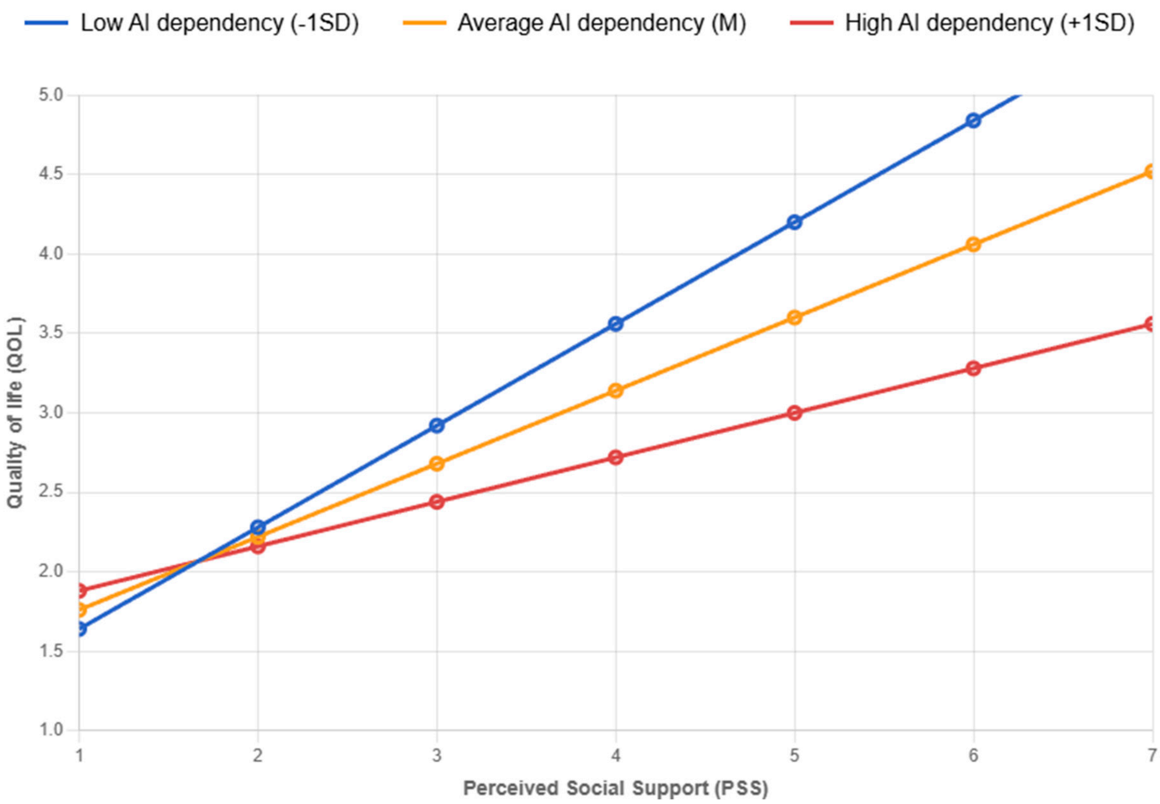

Figure 1. The Moderating effect of AI Dependency on the relationship between Social Support and Quality of Life.

H3: *The Type of Interaction with Generative AI and the Moderation Effect*

For testing this hypothesis, we conducted separate analyses for different types of generative AI usage, focusing on informational and emotional interactions.

Table 6. Descriptive Statistics and Correlations for Types of Generative AI Use.

AI Use Type	M (SD)	1	2	3	4	5
1. Informational	5.63 (1.21)	-				
2. Professional	5.27 (1.36)	.61***	-			
3. Emotional	3.48 (1.73)	.22***	.27***	-		
4. Recreational	4.70 (1.52)	.35***	.29***	.43***	-	
5. GAID-Total	2.71 (1.05)	.21***	.19**	.46***	.40***	-

*Note: *p < .05, **p < .01, **p < .001.*

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We observe that emotional use of generative AI has the strongest correlation with the total score of AI dependency ($r = .46$, $p < .001$), suggesting that this type of use might be more closely linked to the development of dependency.

Table 7. Moderating effects of Informational vs. Emotional use on the relationship between Social Support and Quality of Life.

Predictors	Model with Informational Use β (SE)	Model with Emotional Use β (SE)
Step 1		
PSSS-Total	.45*** (.04)	.46*** (.04)
AI Use (informational/emotional)	.06 (.04)	-.13** (.04)
R^2	.22***	.23***
Step 2		
PSSS-Total	.45*** (.04)	.47*** (.04)
AI Use (informational/emotional)	.05 (.04)	-.14** (.04)
PSSS × AI Use	-.04 (.04)	-.20*** (.04)
ΔR^2	.00	.04***
Total R^2	.22***	.27***

* Note: Values represent standardized beta coefficients with standard errors in parentheses. ** p < .01, *** p < .001.

The results reveal a significant difference between the moderating effects of the two types of usage:

1. Informational use does not significantly moderate the relationship between social support and quality of life ($\beta = -.04$, $p > .05$).
2. Emotional use significantly and negatively moderates this relationship ($\beta = -.20$, $p < .001$), adding 4% additional explained variance.

To better understand the moderating effect of emotional use, we calculated the conditional effects at three levels of emotional use of AI.

Table 8. Conditional effects of Social Support on Quality of Life at different levels of emotional AI use.

Level of Emotional Use	b (95% CI)	p
Low (-1SD)	.63 (.52, .74)	<.001
Medium (M)	.47 (.39, .55)	<.001
High (+1SD)	.31 (.19, .43)	<.001

The results indicate a progressive attenuation of the relationship between social support and quality of life as the intensity of emotional AI use increases, from a strong effect at low levels ($b = .63$) to a significantly diminished effect at high levels ($b = .31$).

Table 9. Comparison between the moderating effects of different types of Generative AI usage.

AI Usage Type	Interaction Coefficient (β)	ΔR^2	p
Informational	-.04	.00	.32
Professional	-.07	.01	.11
Emotional	-.20	.04	<.001
Recreational	-.14	.02	<.01

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This comparison highlights that only emotional and recreational use of generative AI significantly moderates the relationship between social support and quality of life, with a stronger effect for emotional use.

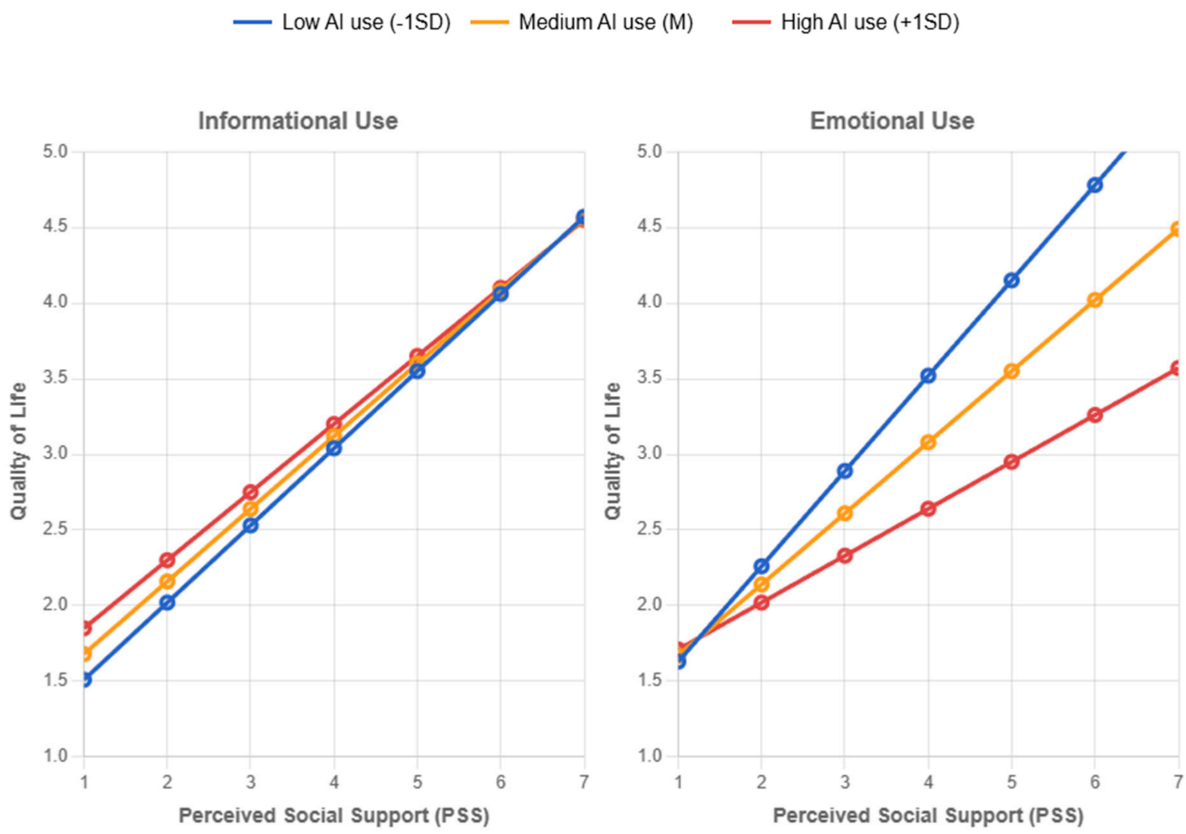

Figure 2. Comparison Between the Moderating Effects of Informational vs. Emotional Use of AI.

The results confirm hypothesis 3, demonstrating that the type of interaction with generative AI significantly influences the nature of the moderation effect:

1. Informational and professional use do not moderate the relationship between social support and quality of life.
2. Emotional use significantly and negatively moderates this relationship.
3. Recreational use presents a significant moderating effect, although less pronounced than that of emotional use.

Additional analyses—moderated mediation

To explore the mechanisms that might explain the observed differences, we tested a moderated mediation model. In this model, we examined whether the type of use influences the relationship between social support and quality of life through AI dependency.

In the emotional use model (Figure 3), there is a significant mediation effect through AI dependency: emotional use significantly increases dependency ($a = .28$, $p < .001$), which in turn negatively moderates the relationship between social support and quality of life ($b = -.19$, $p < .001$). In contrast, the informational use model (Figure 4) does not present such a mediation effect: informational use does not have a significant influence on dependency ($a = .08$, $p > .05$), and the indirect effect is nonsignificant.

These results explain the mechanism through which emotional use, but not informational use, interferes with the benefits of social support for quality of life. Emotional use contributes to the development of dependency, which diminishes the individual's ability to benefit from traditional social support.

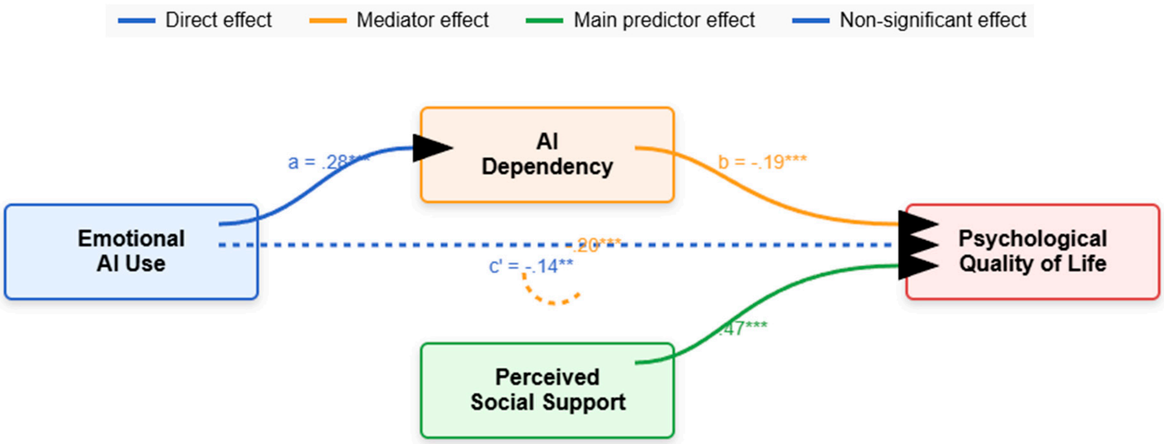

Figure 3. Model for Emotional Use of AI.

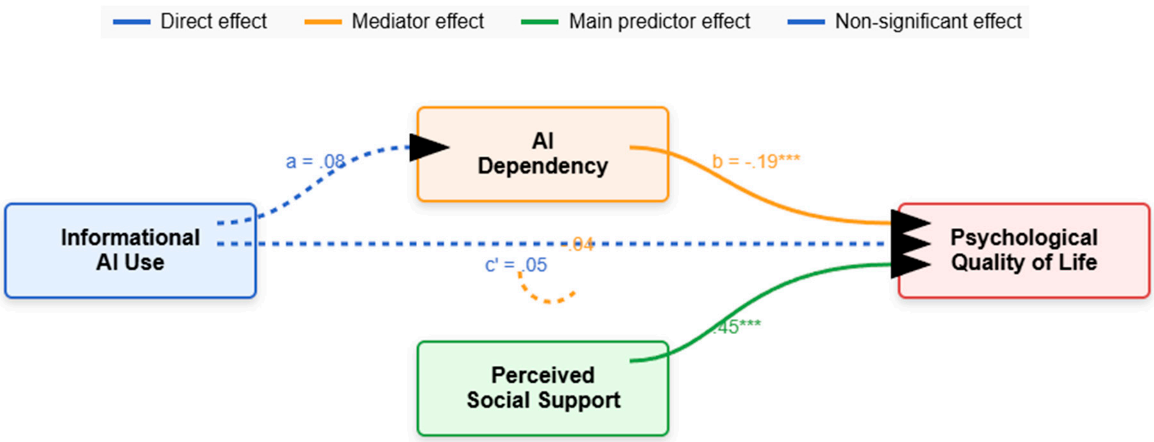

Figure 4. Model for Informational Use of AI.

5. Conclusions

Our study highlighted three main findings: (1) social support is a robust predictor of quality of life in all domains evaluated; (2) this beneficial relationship is significantly attenuated at high levels of generative AI dependency; and (3) the type of AI use significantly influences this moderation effect, with emotional and recreational use having a negative impact, while informational and professional use do not show this effect. The moderated mediation analysis revealed the mechanism through which emotional use, but not informational use, interferes with the benefits of social support: emotional use contributes to the development of AI dependency, which in turn diminishes the individual's ability to benefit from traditional social support.

Theoretical implications. Our results extend the social compensation theory in the digital era, suggesting that using generative AI as an emotional substitute may undermine, rather than augment, the benefits of authentic social interactions. At the same time, they support the concept of „social AI paradox"—although AI can simulate social interactions, dependency on it reduces the ability to benefit from real social support.

Practical Implications

1. Individual users should be aware of the types of interactions with AI and monitor signals of dependency, especially when AI is used for emotional support.
2. AI developers should design systems that complement, not replace, authentic human relationships and integrate mechanisms that encourage healthy use.

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3. Mental health practitioners should include the use of generative AI in the assessment protocols of young people, especially for emotional purposes.

Limitations and Future Directions

Our study presents three main limitations: the cross-sectional design which restricts causal inferences, the predominantly university sample which reduces generalizability, and measurements based on self-reporting.

Future research would benefit from longitudinal approaches to examine changes over time, experimental studies to establish causal relationships, and deeper investigations regarding the effects of different types of AI and contexts of use.

In conclusion, the results do not suggest rejection of generative AI but emphasize the importance of its conscious and balanced use. Although it represents a valuable tool for informational and professional purposes, dependency on AI for satisfying emotional needs can undermine the benefits of authentic social support. It is essential to maintain a critical approach, leveraging the benefits of technology without compromising human relationships that remain fundamental to our well-being.

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