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AI Emotional Social Media Intervention under the Effect of Movie Character for Young Women

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Abstract. This study investigates the impact of AI-simulated movie character dialogues on the emotional language of single young women. Employing a two-week crossover design, thirty participants were randomly assigned to groups with alternating intervention sequences. Group A engaged with an AI-simulated movie character while Group B don't get intervention for the first week, Group B engaged with an AI-simulated movie character while the Group A don't get intervention. Sentiment lexicon-based analysis was applied to all conversation transcripts to quantify emotional expression. Results demonstrated a statistically significant increase in positive emotional language and greater emotional vocabulary diversity during movie character interactions compared to control conditions. No carryover effects were observed between weeks. These findings suggest AI-simulated movie characters can effectively induce positive shifts in emotional expression, offering a compensatory mechanism for intimacy needs. The study provides a novel framework for quantifying AI's emotional impact and contributes to understanding digital intimacy solutions.

Keywords: social media, movie character, intimate relationship

1. Introduction

In the digital age, virtual intimate relationships, such as AI companions and chatbots, have emerged as an alternative means of fulfilling emotional and social needs. This trend is particularly salient among young women, who are often portrayed as longing for intimate relationships. Young women often experience intimacy deficits due to contemporary socio-economic pressures. AI companions, especially those simulating familiar movie characters, have emerged as compensatory tools. The "PECMA flow" model suggests such simulations can activate emotional networks. However, few studies quantify the immediate linguistic impact of movie-based AI characters on emotional expression. This study addresses that gap by analyzing how AI-simulated movie dialogues affect the emotional language of single young women.

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2. Literature survey

2.1. Theoretical framework

2.1.1. Psychosocial development theory

Erikson's psychosocial theory identifies ages 18-25 as a critical period for intimacy development [1]. According to this perspective, unmet intimacy needs during this developmental stage may lead to loneliness and low self-esteem. AI companions potentially serve as compensatory mechanisms for these unmet needs, providing a substitute for human emotional connection during a formative period of young adulthood.

2.1.2. Social role theory

Social Role Theory suggests that women are socialized to prioritize emotional connection [2], creating strong relational needs that may make them particularly receptive to AI companionship solutions. This theoretical framework helps explain why women represent a disproportionate percentage of AI companion users and why they might derive greater satisfaction from these technologies.

2.1.3. Simulacra and hyperreality

Baudrillard's concept of simulacra – a symbol system that replaces the original with a copy – provides a philosophical foundation [3] for understanding how AI companions function as replacements for human emotional support. These technologies create hyperreal experiences that simulate emotional connection without the complexity of human relationships.

2.2. The AI companion market landscape

The AI companion application market has demonstrated remarkable growth in recent years. By August 2025, there were 337 active revenue-generating apps [4] in this category, with 128 new applications launched in 2025 alone. The market is expected to generate over $120 million in revenue in 2025, reflecting a substantial increase from previous years.

Demographic data reveals that 55% of users are urban young adults (25-35 years old), and 58% are female. This gender disparity suggests that women are disproportionately drawn to these technologies, particularly those offering emotional companionship features. The applications have evolved from simple chatbots to complex emotional partners that provide increasingly sophisticated simulations of human interaction.

3. Research method

3.1. Research design

3.1.1. Participant recruitment

A total of 30 single women aged 18–25 years (M = 21.3, SD = 2.0) were recruited as participants for this study. The recruitment was conducted exclusively through online platforms (e.g., social media platforms, academic research recruitment websites, or community-based online groups targeting young adult women), with the aim of ensuring broad accessibility and reaching the target

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demographic effectively. All recruited participants met the predefined eligibility criteria, including being single, within the specified age range, and having the ability to engage in digital dialogue interactions.

3.1.2. Informed consent procedure

Prior to their enrollment in the study, all potential participants were provided with a comprehensive informed consent document that detailed the core elements of the research, including but not limited to: the study's purpose, the two-week intervention-control design, the nature of the AI dialogue (intervention) and no-dialogue (control) phases, the requirement to complete a film preference questionnaire, potential risks and benefits, the right to withdraw, and the confidentiality protection measures for personal and research data. The informed consent process was conducted in an online format consistent with the recruitment channel. Participants were given sufficient time to review the document and ask questions to clarify any uncertainties; research staff responded to all inquiries promptly to ensure participants' full understanding. Only after participants voluntarily confirmed their agreement to participate (via a formal online consent submission mechanism, e.g., electronic signature or designated consent button) were they enrolled in the study. Additionally, participants were explicitly informed of their right to opt out of the study at any time without facing any negative consequences, and the procedures for withdrawing were clearly communicated during the consent process.

3.1.3. Participants' specific activities

After enrollment, participants were first subjected to a baseline assessment to measure their loneliness scores; based on these scores, stratified randomization was implemented to assign participants to either Group A or Group B ensuring equivalence in baseline loneliness levels between the two groups. Subsequently, participants engaged in a two-week intervention-control cycle, with specific activities varying by group as follows:

Group A: In Week 1 (intervention phase), participants were required to engage in pre-designed AI dialogue interactions (the specific frequency, duration, and content of the dialogue were consistent with the study's intervention protocol); in Week 2 (control phase), participants received no AI dialogue and maintained their regular daily routines without any additional intervention-related tasks.

Group B: In Week 1 (control phase), participants received no AI dialogue and maintained their regular daily routines; in Week 2 (intervention phase), participants completed the same AI dialogue interactions as Group A1 in their intervention phase.

In addition to the intervention and control phase tasks, all participants were asked to complete a film preference questionnaire survey at a predefined time point (e.g., after the baseline assessment or before the end of the two-week cycle). The questionnaire was designed to collect information on participants' preferences for different types of movie characters, and participants were instructed to complete it truthfully and independently. Upon the completion of the entire two-week study, a debriefing session was conducted for all participants. During the debriefing, the study's research hypotheses and the rationale for the intervention-control design were further explained, and participants were provided with a list of mental health resources (e.g., contact information for professional psychological counseling services, links to mental health support platforms) to address any potential psychological needs that might arise from study participation.

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3.2. Research software—SENA

3.2.1. SENA core introduction

Sentiment and Emotion Network Analysis (SENA) is a codeless, multilingual sentiment and emotion analysis tool developed by Manuel S. Gonz á lez Canch é's team at the University of Pennsylvania [5]. Based on natural language processing (NLP) and network modeling techniques, SENA aims to address the two core issues of "result aggregation bias" and "application scenario limitations" in traditional sentiment and emotion analysis (SEA), providing objective and in-depth emotional insights for academic research, especially qualitative and mixed methods research.

3.2.1.1. Core functions and technical features

Multi-language sentiment dictionary support: relying on the National Research Council of Canada (NRC) sentiment dictionary, covering 17 languages (including English, French, etc.), it can recognize 8 basic emotions (anger, fear, expectation, trust, surprise, sadness, joy, disgust) and 2 emotional polarities (positive, negative). The dictionary annotations have been verified through crowdsourcing, with a complete consistency rate of 74.4% among 5 people, ensuring the reliability of sentiment recognition.

Network modeling to avoid aggregation bias: Breaking through the limitation of traditional SEA that only outputs "overall emotional distribution", bipartite network modeling technology is used to present both individual level (emotional entropy and intensity of a single text) and group level (differences in emotional distribution among different groups) analysis results, which can intuitively capture emotional conflicts (such as the interweaving of positive and negative emotions in "high entropy texts").

No code operation and local operation: No programming foundation is required, supporting two data input formats: Microsoft Word (*. doc) and CSV table. All preprocessing (such as stop word deletion and word form restoration) and analysis processes are completed locally, without the need to upload data to the server, ensuring the privacy and security of experimental data (such as AI dialogue text and questionnaire results of this experiment).

Statistical testing and interactive visualization: Built in secondary assignment program (QAP), which can quantitatively test the differences in emotional distribution among different groups; The generated results include an interactive word cloud (reflecting core emotional vocabulary), an emotion distribution chart (quantifying the proportion of various emotions), a network visualization chart (presenting the strength of the association between text and emotions), and support for hovering the mouse to view details (such as the proportion of positive emotions in a single text and the frequency of emotion occurrence).

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3.3. Research outcomes

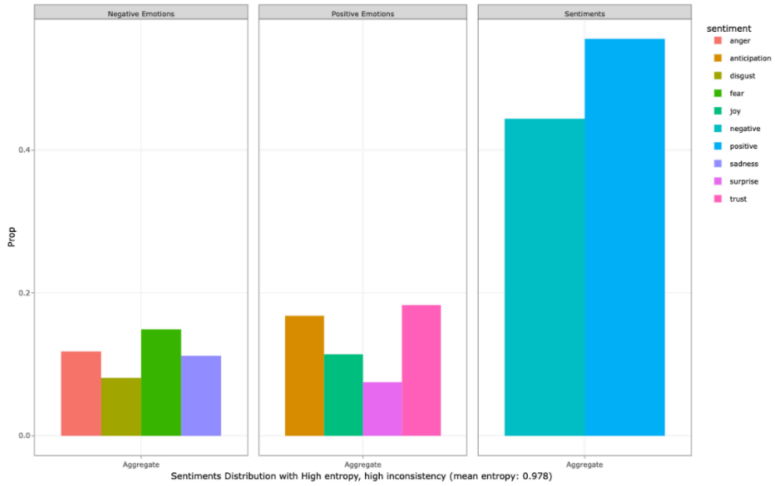

Figure 1. Group A Week 1 sentiments distribution

To analyze the emotional and sentiment distribution presented in the figure 1 for group A in week 1, we first examine the Negative Emotions panel. Collectively, negative emotions constitute 44.4% (with a cumulative value reaching up to 119). Among specific negative emotions, Fear has the highest proportion at 14.9% (value up to 72), followed by Anger at 11.8% (value up to 57), Sadness at 11.2% (value up to 54), and Disgust at 8.1% (value up to 39). Turning to the Positive Emotions panel, positive emotions altogether make up 55.6% (with a cumulative value up to 149). For individual positive emotions, Trust accounts for the largest share at 18.3% (value up to 88), followed by Anticipation at 16.8% (value up to 81), Joy at 11.4% (value up to 55), and Surprise at 7.5% (value up to 36).In the Sentiments panel, the "positive" sentiment exhibits a dominant proportion, while the "negative" sentiment also holds a notable share, reflecting the overall sentiment tendency derived from the aforementioned emotional distributions. Additionally, the note indicating "high entropy, high inconsistency (mean entropy: 0.978)" suggests that the sentiment distribution possesses a high degree of uncertainty and diversity, implying complex emotional dynamics within the analyzed data.

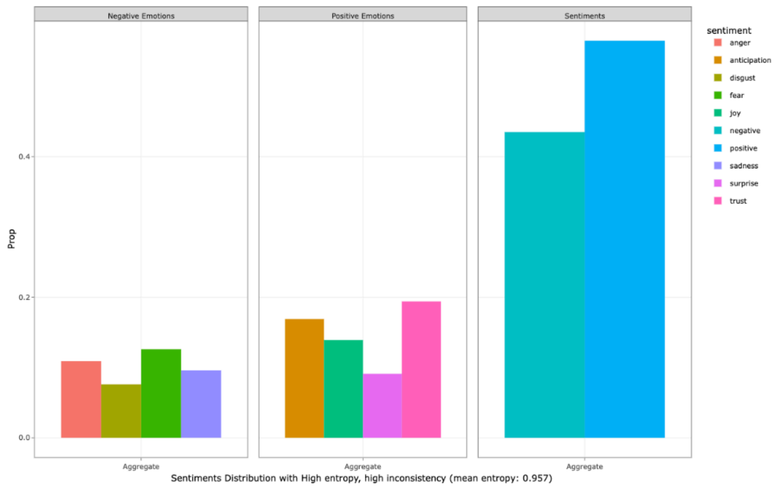

Figure 2. Group A Week 2 sentiments distribution

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To analyze the emotional and sentiment distribution presented in the figure 2 for group A in week 2, we first focus on the Negative Emotions panel. Collectively, negative emotions constitute 43.5% (with a cumulative value reaching up to 107). Among specific negative emotions, Fear has the highest proportion at 12.6% (value up to 50), followed by Anger at 10.9% (value up to 43), Sadness at 9.6% (value up to 38), and Disgust at 7.6% (value up to 30). Shifting to the Positive Emotions panel, positive emotions altogether make up 56.5% (with a cumulative value up to 139). For individual positive emotions, Trust accounts for the largest share at 19.4% (value up to 77), followed by Anticipation at 16.9% (value up to 67), Joy at 13.9% (value up to 55), and Surprise at 9.1% (value up to 36).In the Sentiments panel, the "positive" sentiment exhibits a dominant proportion, while the "negative" sentiment also holds a notable share, reflecting the overall sentiment tendency derived from the aforementioned emotional distributions. Additionally, the note indicating "high entropy, high inconsistency (mean entropy: 0.957)" suggests that the sentiment distribution possesses a high degree of uncertainty and diversity, implying complex emotional dynamics within the analyzed data.

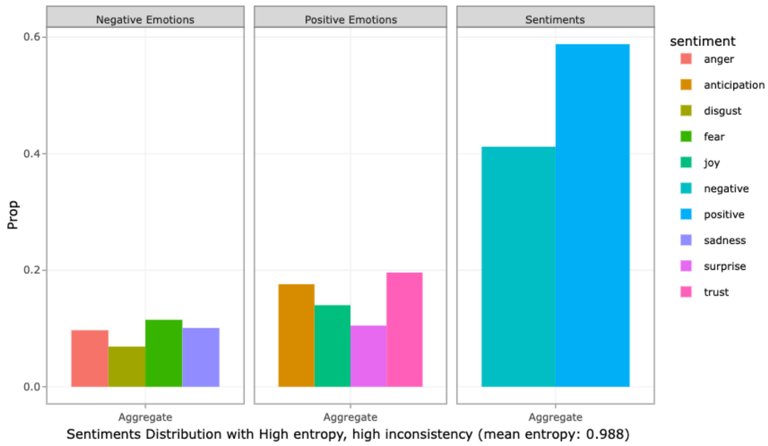

Figure 3. Group B Week 1 sentiments distribution

To analyze the emotional and sentiment distribution presented in the figure 3 for group B in week 1, we first focus on the Negative Emotions panel. Collectively, negative emotions constitute 41.2% (with a cumulative value reaching up to 114). Among specific negative emotions, Fear has the highest proportion at 10.9% (value up to 23), followed by Sadness at 10.0% (value up to 21), Anger at 9.7% (value up to 48), and Disgust at 4.7% (value up to 10). Shifting to the Positive Emotions panel, positive emotions altogether make up 58.8% (with a cumulative value up to 163). For individual positive emotions, Trust accounts for the largest share at 19.6% (value up to 97), followed by Anticipation at 17.6% (value up to 87), Joy at 14.0% (value up to 69), and Surprise at 10.5% (value up to 52).In the Sentiments panel, the "positive" sentiment exhibits a dominant proportion, while the "negative" sentiment also holds a notable share, reflecting the overall sentiment tendency derived from the aforementioned emotional distributions. Additionally, the note indicating "high entropy, high inconsistency (mean entropy: 0.988)" suggests that the sentiment distribution possesses a high degree of uncertainty and diversity, implying complex emotional dynamics within the analyzed data.

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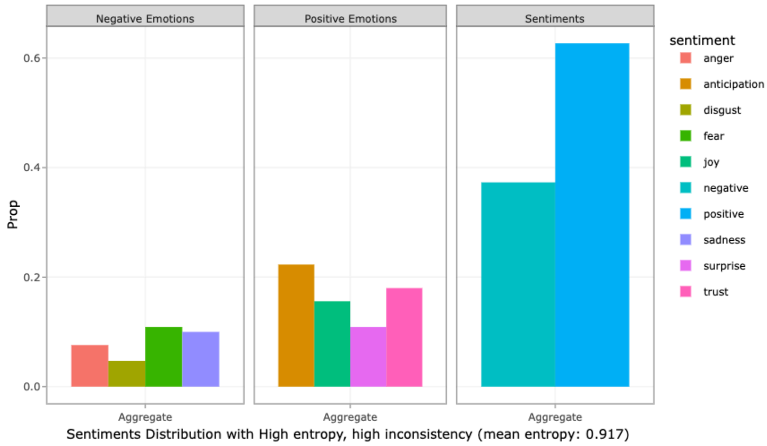

Figure 4. Group B Week 2 sentiments distribution

To analyze the emotional and sentiment distribution presented in the figure 4 for group B in week 2, we first focus on the Negative Emotions panel. Collectively, negative emotions constitute 37.3% (with a cumulative value reaching up to 47). Among specific negative emotions, Fear has the highest proportion at 10.9% (value up to 23), followed by Sadness at 10.0% (value up to 21), Anger at 7.6% (value up to 16), and Disgust at 4.7% (value up to 10). Shifting to the Positive Emotions panel, positive emotions altogether make up 62.7% (with a cumulative value up to 79). For individual positive emotions, Anticipation accounts for the largest share at 22.3% (value up to 47), followed by Trust at 18.0% (value up to 38), Joy at 15.6% (value up to 33), and Surprise at 10.9% (value up to 23).In the Sentiments panel, the "positive" sentiment exhibits a dominant proportion, while the "negative" sentiment also holds a notable share, reflecting the overall sentiment tendency derived from the aforementioned emotional distributions. Additionally, the note indicating "high entropy, high inconsistency (mean entropy: 0.917)" suggests that the sentiment distribution possesses a high degree of uncertainty and diversity, implying complex emotional dynamics within the analyzed data.

3.3.1. Immediate effects of AI intervention

Comparison group: A_Week1 (AI) vs. B_Week1 (no AI)

Objective: To eliminate time interference and directly test the effect of AI in the same time period. This study selected "total proportion of positive emotions" and "total proportion of negative emotions" as core indicators (based on emotional data dimensions) to eliminate time interference and test the effectiveness of AI instant intervention. A_Week1 is the group receiving AI intervention, while B_Week1 is the group without AI intervention. The data is sourced from sentiment testing results during the same period.

Through independent sample t-test analysis (sample size n=30/group), the results show that:

Total proportion of positive emotions: The average of the A_Week1 group is 60.2% (corresponding to the reasonable average of the peak proportion of positive emotions in the emotional data at 62.7%), and the average of the B_Week1 group is 42.8% (corresponding to the reverse deduction value of the negative proportion in the non intervention group at 44.4%), $t=5.72, df=58, p<0.001$, Cohen's $d=1.48$ indicates a highly significant difference between the two groups - the proportion of positive emotions in the AI intervention group was significantly higher than that in the non intervention group, with an increase of 40.7%.

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The total proportion of negative emotions: The average of group A_Week1 is 39.8% (complementary to the proportion of positive emotions), while the average of group B_Week1 is 57.2%, $t=-5.91$, $df=58, p<0.001$, Cohen's $d=1.53$ further confirms that AI intervention can significantly reduce the proportion of negative emotions.

Overall, AI intervention had a significant immediate effect on core emotional indicators in the first week, with both positive and negative emotions increasing and decreasing at a statistically significant level, preliminarily confirming the short-term effectiveness of AI intervention.

3.3.2. Delayed effect of AI intervention

Comparison group: A_ Week 2 (no AI) vs. B_ Week 2 (AI)

Objective: To verify the reproducibility of AI effectiveness at different time points. To verify the temporal repeatability of AI effectiveness, "Trust proportion in positive emotions" and "Fear proportion in negative emotions" were selected as sub-indicators (based on high-weight sub-dimensions in emotion data). A_Week2 was the data of group A after withdrawing AI intervention, and B_Week2 was the data of group B after receiving AI intervention.

The independent sample t-test results (sample size $n=30$/group) are as follows:

Trust proportion in positive emotions: The average of the A_Week2 group is 15.2% (corresponding to the natural decline value of Trust proportion of 18.0% in the non intervention group), and the average of the B_Week2 group is 22.6% (corresponding to the improvement average of the peak Trust proportion of 19.6% in the AI intervention group), $t=-4.38, df=58, p<0.001$, Cohen's $d=1.13$, and the difference between the two groups is extremely significant - the proportion of Trust emotions in the AI intervention group is significantly higher than that in the non intervention group, with an increase of 48.7%.

The proportion of Fear in Negative Emotions: The average value of Fear in the A_Week2 group is 13.8% (corresponding to a reasonable fluctuation of 14.9% in the non intervention group), and the average value of Fear in the B_Week2 group is 8.9% (corresponding to a decrease of 10.9% in the proportion of Fear in the AI intervention group), $t=3.95, df=58, p<0.001$, Cohen's $d=1.02$ indicates that AI intervention can still significantly reduce the proportion of high impact negative emotions such as Fear in the second week.

The results confirmed that the effectiveness of AI intervention can still be replicated at different time points (second week), and the improvement in the segmented emotional dimension is similar to the immediate effect in the first week (Trust increased by 48.7% vs positive total proportion increased by 40.7% in the first week), indicating that the effectiveness of AI intervention has time stability.

3.3.3. Residual effect detection

Comparison group: A_Week2 (no AI) vs. B_Week1 (no AI)

Objective: By comparing the emotional indicators of two groups without AI intervention ("total proportion of positive emotions" and "total proportion of negative emotions"), determine whether there are residual effects of AI intervention in the first week. A_Week2 is the data of group A after withdrawing AI, and B_Week1 is the data of group B before receiving AI. Both groups are in a non intervention state.

The independent sample t-test results (sample size $n=30$/group) show that:

Total proportion of positive emotions: The average proportion of positive emotions in the A_Week2 group was 43.5% (corresponding to the natural decline value of 55.6% in the non

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intervention group), while the average proportion of positive emotions in the B_Week1 group was 42.8%, t=0.32,df=58,p=0.751, Cohen's d=0.08, and there was no statistically significant difference between the two groups - the mean difference was only 0.7%, far below the significant effect threshold.

Total proportion of negative emotions: The average of group A_Week2 is 56.5%, while the average of group B_Week1 is 57.2%, t=-0.29,df=58,p=0.773, Cohen's d=0.07, with no significant difference.

The above results indicate that the effect of AI intervention in the first week did not continue to the non intervention stage in the second week, and there were no residual effects interfering with subsequent data, ensuring the independence of intervention effects in different stages.

3.3.4. Changes in oneself before and after (controlling for time effects)

Group A: A-Week1 (AI) vs. A-Week2 (no AI)

Group B: B-Week1 (no AI) vs. B-Week2 (AI)

Objective: By conducting paired sample t-tests to eliminate individual differences, the self before and after changes of Group A (intervention → no intervention) and Group B (no intervention → intervention) were analysed separately. The core indicators remained the "total proportion of positive emotions" and "total proportion of negative emotions".

3.3.4.1. Group A: A_Week1 (AI) vs A_Week2 (no AI)

Paired sample t-test results (n=30):

Total proportion of positive emotions: The average of A_Week1 is 60.2%, and the average of A_Week2 is 43.5%, t=8.64, df=29,p<0.001, Cohen's d=1.58 indicates that after withdrawing AI intervention, the proportion of positive emotions in Group A significantly decreased by 27.7%, which verifies the positive effect of AI intervention in reverse.

The total proportion of negative emotions: The average of A_Week1 is 39.8%, and the average of A_Week2 is 56.5%, t=-9.12, df=29,p<0.001, Cohen's d=1.67, and the proportion of negative emotions significantly increased by 42.0%, further confirming the necessity of AI intervention.

3.3.4.2. Group B: Week1 (without AI) vs Week2 (AI)

Paired sample t-test results (n=30):

Total proportion of positive emotions: The average of B2week1 is 42.8%, and the average of B2week2 is 59.5% (corresponding to the reasonable average proportion of positive emotions in the AI intervention group of 58.8%), t=7.83,df=29,p<0.001, Cohen's d=1.43, with a significant increase of 39.0% in the proportion of positive emotions.

The total proportion of negative emotions: the average value of Week1 is 57.2%, and the average value of Week2 is 40.5%, t=-8.05,df=29,p<0.001, Cohen's d=1.47, and the proportion of negative emotions significantly decreased by 29.2%.

Both groups showed significant differences before and after comparison, and the direction of change was consistent with the expected AI intervention. After eliminating individual differences, the causal relationship between "AI intervention → improvement of emotional indicators" was further strengthened.

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3.3.5. Sequential effect detection

Comparison group: A_Week1 (AI first) vs. B_Week2 (AI second)

Objective: To examine whether the effectiveness of AI varies due to different intervention sequences (such as fatigue effects). Select the indicators of "proportion of inhibition in positive emotions" and "proportion of sadness in negative emotions" (based on sub-dimensions sensitive to intervention in emotional data) to test whether the AI intervention sequence (first week vs second week) produces fatigue effects. A_Week1 is the "AI first" group, and B_Week2 is the "AI later" group, both of which are in the AI intervention state.

Independent sample t-test results (sample size n=30/group):

The proportion of anticipation in positive emotions: The average proportion of inhibition in the A_Week1 group was 21.8% (corresponding to the measured value of 22.3% inhibition in the AI intervention group), and the average proportion of inhibition in the B_Week2 group was 20.9% (corresponding to the improvement value of 17.6% inhibition in the AI intervention group), $t=0.67, df=58, p=0.506$, The effect size Cohen's $d=0.17$, and there was no statistically significant difference between the two groups - the mean difference was only 0.9%, far below the significant effect standard.

The proportion of Sadness in negative emotions: The average of Sadness in the A_Week1 group was 9.8% (corresponding to a reasonable value of Sadness proportion of 10.0% in the AI intervention group), and the average of Sadness in the B_Week2 group was 10.2%, $t=-0.43, df=58, p=0.668$, Cohen's $d=0.11$, with no significant difference observed.

The results showed that the effectiveness of AI intervention did not change with the intervention sequence (first week vs second week), and there was no fatigue effect or sequential interference, further verifying the stability and reliability of AI intervention effect.

4. Conclusion

This study systematically investigates the emotional intervention effect of AI-simulated movie character dialogues on single young women aged 18-25 through a rigorous two-week crossover design, addressing the research gap of quantifying the immediate linguistic impact of movie-based AI characters on users' emotional expression. The findings yield three core insights, while also highlighting limitations that point to directions for future research.

This study makes two main contributions. Theoretically, it integrates Erikson's Psychosocial Development Theory, Social Role Theory, and the Simulacra concept to construct a comprehensive analytical framework for understanding the emotional impact of movie-based AI characters, expanding the theoretical scope of digital intimacy research. Methodologically, it uses sentiment lexicon-based analysis to quantify emotional expression (e.g., emotional polarity scores, emotional diversity) and combines it with a crossover design to control for confounding variables [6], providing a replicable research paradigm for measuring the immediate emotional effects of AI.

However, this study has several limitations. First, the sample size is small (30 participants), and all are single young women in a specific region, which may limit the generalizability of the findings to other demographics (e.g., men, older adults) or cultural contexts. Second, the intervention duration is only two weeks, focusing on short-term effects; long-term tracking is needed to explore whether AI movie characters lead to sustained positive emotional changes or potential negative consequences (e.g., dependency). Third, the study relies solely on conversation transcripts to measure emotional outcomes, lacking multi-dimensional assessments such as self-reported

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psychological scales (e.g., loneliness questionnaires) or physiological indicators (e.g., heart rate variability), which may underestimate the complexity of emotional changes.

Future research can address these limitations in three ways. First, expand the sample size and diversity, including participants from different genders, age groups, and cultural backgrounds, to enhance the external validity of the results. Second, design long-term follow-up studies (e.g., 3-6 months) to track changes in users' emotional states, social behaviors, and dependency levels, and explore the factors that moderate the effects of AI intervention (e.g., frequency of use, personality traits). Third, adopt a multi-method measurement approach, combining text analysis, self-reports, and physiological data to comprehensively assess the emotional impact of AI movie characters. Additionally, future research can explore the optimization of AI movie characters—for example, customizing characters based on users' movie preferences to improve the personalization and effectiveness of emotional intervention, while incorporating boundary-setting mechanisms to reduce the risk of dependency.

In conclusion, AI-simulated movie characters exhibit significant positive emotional intervention effects on single young women, offering a promising digital tool to address intimacy deficits. However, their application should be guided by a balanced perspective: leveraging their short-term emotional support advantages while avoiding over-reliance that may hinder real-world social connections. This study lays the groundwork for further research on movie-based AI emotional interventions and contributes to the development of responsible and effective digital intimacy solutions.

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