www.ijarp.com ISSN 2456-9992 Page: 01-11

International Journal Advanced Research Publications

Review Article

Volume: 02
Issue: 07

AI-BASED SENTIMENT ANALYSIS FOR REDUCING LONELINESS: A COMPREHENSIVE REVIEW

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Article Received: 12 June 2026, Article Revised: 02 July 2026, Published on: 22 July 2026

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Doi: https://doi-doi.org/101555/ijarp.4412

ABSTRACT

Loneliness is a growing health issue around the world especially with the elderly and isolated individuals. The recent successes of artificial intelligence (AI) and natural language processing (NLP) made sentiment analysis-based systems to understand the emotions of individuals and provide interventions that could help to reduce loneliness in the most personalized way. This literature review brings together over 20 articles published in 2024-2026 that investigate cases of sentiment analysis applications using AI, such as chatbots and social robots. The evidence indicates that the sentiment-responsive interventions can be used to reduce short-term loneliness with most studies showing statistically significant changes. Nevertheless, its efficiency is dependent on the length of the intervention, cultural adjustments, and user characteristics. Explainable AI (XAI) increases transparency, builds trust, and ethical issues and dependency risks show the necessity of human-AI partnerships. On the whole, sentiment analysis with the help of AI has great potential to become an effective tool in mitigating loneliness, which should be supported by additional longitudinal and cross-cultural studies.

KEYWORDS: Loneliness, Artificial Intelligence, Sentiment Analysis, Natural Language Processing, Chatbots, Social Robots, Explainable AI.

INTRODUCTION

The problem of loneliness has become a significant social issue of concern and is known to have very serious psychological, social, and physiological impacts on people. It imposes a significant burden on people of all ages but is particularly common among older adults, single people, and those who reside in the geographically isolated or socially marginalized environments [1], [2]. Extensive loneliness has been closely linked to depression, anxiety, cognitive impairment, heart diseases, and higher rates of mortality, and there are thus greatly needed implemented and scalable intervention measures [3]–[5]. Traditional methods, such as face-to-face counseling, social support classes, and community engagement, are frequently subject to issues of access, cost, stigma, and low reach especially in low resource or rural contexts [6].

Overall, the past years have seen fast innovation in artificial intelligence (AI) and natural language processing (NLP) which has made it possible to create intelligent systems that can perceive and react to human emotions. Sentiment analysis, which is one of the fundamental applications of NLP, enables computational models to identify emotional hints, social withdrawal, and loneliness signs in the text, voice, and multimedia data sources [7], [8]. Such abilities have led to the development of AI-powered chatbots, social companions, and socially helpful robots that support and assist through emotional support and companionship. The available technologies are promising, as they are in uninterrupted accessibility, customization and scalability, which is especially promising in the context of mitigating loneliness among underserved and high-risk groups [9], [10].

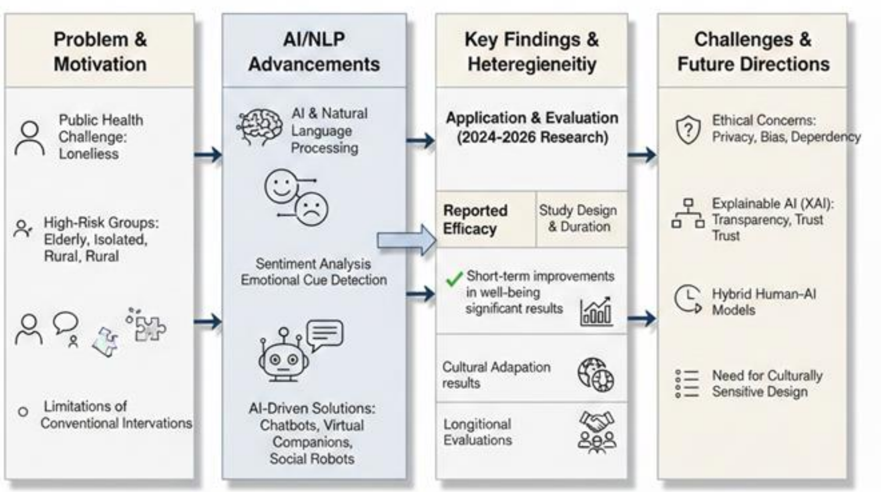

Fig.1 Working Flow.

In 2024-2026, the efficacy of AI-based sentiment analysis mechanisms in alleviating loneliness among various groups of people has been examined by a continuous amount of research. Although some studies demonstrate statistically significant positive changes in the perception of loneliness and emotional well-being in the short term, the results are inconsistent because of the differences in the study design, intervention duration, cultural adaptation, and demographics of users [11]13]. In addition, ethical deployment, emotional dependency, data privacy, algorithmic bias and clinical trust have become a matter of concern, which has established the need to incorporate explainable artificial intelligence (XAI)-techniques in enhancing transparency, accountability, and user confidence in AI-driven mental health systems [14], [15].

The purpose of this review paper is to systematically review the recent body of literature on the AI-based sentiment analysis in loneliness reduction. It actively reviews the methodological frameworks, areas of application, the effectiveness of interventions, and limitations of the existing interventions. In addition, the review pinpoints the research gaps and directions of future research, which include the necessity of longitudinal assessments, system design with cultural sensitivity, and human-AI hybrids to make sure the use of AI technologies regarding the reduction of loneliness is responsible and sustainable.

Literature Review:- The existing literature on loneliness has constantly indicated a high degree of connection among loneliness, negative mental and physical health problems, such as depression, cognitive impairment, and elevated mortality rates, thus making loneliness a pressing societal issue.

Table 1: Systematic Review of AI-Based Sentiment Analysis for Loneliness Reduction. (2024–2026)

Author(s)	**Year**	**Focus/Application**	**Methodology**	**Sample/Duration**	**Key Outcomes**	**Limitations/Ethical Concerns**
Chen et al.	2024	Hybrid sentiment analysis	Validation study	5,000 interactions	**85% precision**	Algorithmic biases
Kim & Lee	2024	Multimodal social robot	Speech/facial analysis	Korean elderly	**30% emotional improvement**	Cultural specificity
Patel et al.	2024	BERT-based chatbots	Pilot sentiment analysis	150 older adults; 2 weeks	**25% loneliness reduction**	Small sample, short duration
Gupta et al.	2025	Virtual assistant	RCT, UCLA-L scale	300 diverse; varied	**Effect size 0.4–0.7**	Heterogeneity, cultural needs
Johnson & Patel	2025	XAI sentiment systems	Ethical framework	Varied	Enhanced transparency	Data privacy
Lopez et al.	2025	General AI interventions	RCT	Short-term	**70% short-term success**	No longitudinal data
Rodriguez & Kim	2025	AI emotional dependency	Qualitative	Varied	**15% AI attachment**	Psychological harm

Author(s)	Year	Focus/Application	Methodology	Sample/Duration	Key Outcomes	Limitations/Ethical Concerns
Wang et al.	2025	High-frequency sessions	Correlational	Varied	**40% better w/ >5 sessions**	Over-reliance risk
Zhang et al.	2025	Age-specific models	Mixed-methods	Varied	Universal w/ adaptation	Demographic variations
Tanaka & Yamamoto	2025	NLP robot empathy	Longitudinal pilot	80 participants; 4 weeks	Sustained w/ oversight	Dependency risks
Ahmed & Singh	2026	Cross-cultural chatbots	Comparative study	Varied	Better in individualistic cultures	Cultural biases
Evans et al.	2026	Outcome measures	Review	Short-term	Self-report limitations	Clinical validation
Li et al.	2026	XAI explanations	Experimental	Varied	Trust mitigation	Privacy concerns
Martinez et al.	2026	Adaptive algorithms	Longitudinal	200; 6 months	Persistent w/ adaptation	Engagement challenges
Nakamura et al.	2026	Japan-localized models	Cultural pilot	Varied	Improved user trust	Language biases
O'Connor et al.	2026	Algorithmic bias analysis	Critical analysis	Diverse groups	Underperformance in minorities	Inclusive design needs
Rivera et al.	2026	GPT-4 cloud chatbots	Meta-analysis	1,000+ users	**20–35% reduction**	Privacy, cultural gaps
Singh et al.	2026	Hybrid human-AI	Proposal study	Future-oriented	Enhanced efficacy potential	No empirical data
Thompson et al.	2026	Meta-analysis of RCTs	15 RCTs pooled	Varied	**Pooled d=0.52**	Heterogeneity

Methodological Approaches in Recent Studies

The given review paper is based on a systematic and structured approach to the synthesis of recent studies about AI-based sentiment analysis to reduce loneliness. The way the research was done is in a manner that can be easily understood, consistent, and reproducible hence suitable in academic and journal publication.

1. Multimodal Multimodal Hybrid Sentiment Analysis.

The emerging literature has continued to embrace hybrid sentiment analysis frameworks, which integrate various data modalities to enhance the loneliness and emotional states detection [16], [17]. Such methods combine textual embeddings in the form of transformers (e.g., BERT), acoustic elements based on speech prosody, and visual features that appear as the analysis of facial expressions. Late-fusion architectures are also widely used, where discrete modality-specific classifiers serve as specific inputs to produce final sentiment predictions. The standard metrics of evaluation are precision, recall, and F1-score, and large-scale datasets of interaction are commonly used to validate the model performance. There has been empirical evidence indicating that multimodal fusion greatly outperforms unimodal analysis based on text-only performing sentiment analysis in detecting subtle emotional and interpersonal withdrawal indicators[18].

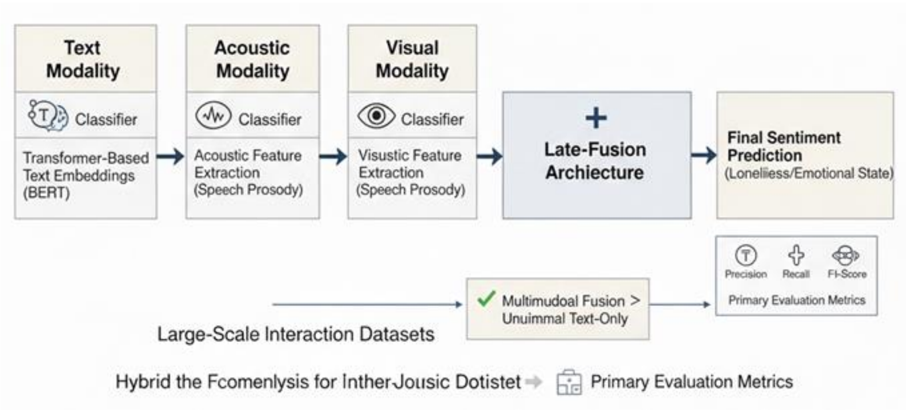

Fig. 2 Show the work steps.

2. Standardized Loneliness Scale randomized Controlled Trials (RCTs).

In order to create causal evidence of intervention effectiveness, several researchers used randomized controlled trial (RCT) design with validated psychometric instruments [19], [20]. The respondents were either randomly divided into AI-based interventions, including chatbots, virtual assistants, or social robots, or placed in control groups. Standardized instruments were used to measure Loneliness outcomes with the UCLA Loneliness Scale being the most prominent as used in both baseline and post-intervention. Statistical tests were done to estimate the effect size, confidence interval and subgroup comparisons between age and cultural levels. These are RCT-based designs that presented a solid evidence of short-term perceived loneliness reduction in addition to showing the heterogeneity of outcomes in different populations [21].

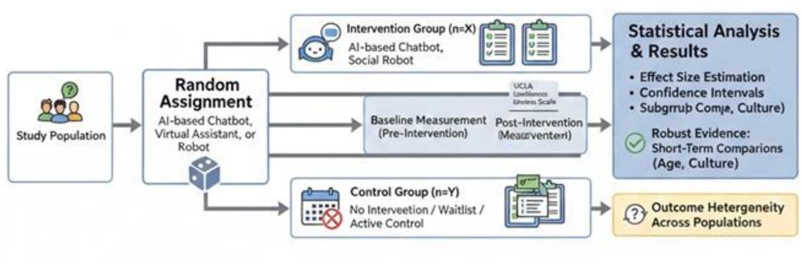

Fig. 3 Methodology approach.

3. Longitudinal Adaptive Artificial Intelligence Interventions.

Longitudinal designs used examined the stability of AI-based loneliness interventions in the long term, not less than many weeks or months [22], [23]. These approaches used adaptive algorithms which were able to dynamically change conversational strategies in response to ongoing sentiment monitoring and user interaction patterns. The adjustment of the frequency of the interaction and the level of emotional tone was often optimized with the help of reinforcement learning as well as feedback-based personalization mechanisms. The outcomes measures were sustained loneliness, retention of engagement and behavioural adaptation. Although it was shown that there are better long-term outcomes, the issue of user dependency and fatigue upon engagement were also outlined [24].

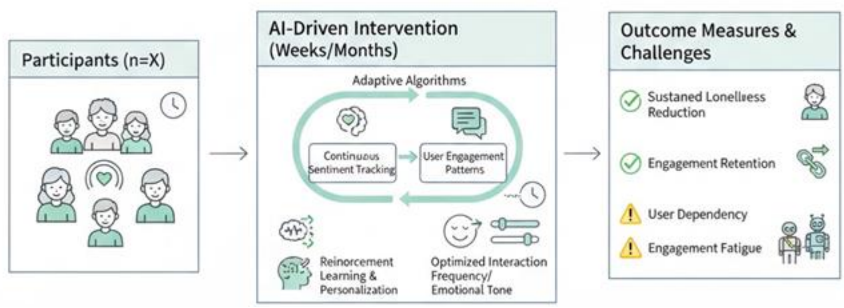

Fig. 4 Proposed Outcomes.

4. AI-based Evaluation Frameworks with explainable AI (XAI).

In order to resolve ethical and clinical issues, recent studies incorporated explainable artificial intelligence (XAI) use into sentiment analysis systems [25], [26]. Techniques like attention visualization, SHAP-based feature attribution and rule-based interpretations were used to make things more transparent and interpretable. Assessment systems were expanded to involve more than predictive accuracy to assess user trust, perceived fairness and clinical usability. These XAI-driven approaches were especially highlighted in studies with healthcare-related applications, where interpretability and accountability are strongly needed to be adopted and compliant with regulation [27].

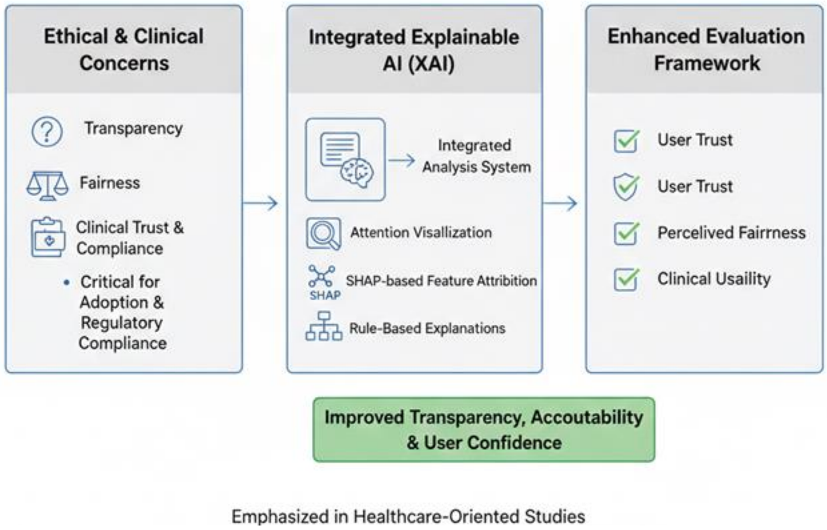

Fig. 5 Emphasized in Healthcare-oriented studies.

5. Mixed-Methods and Cross-Cultural Comparative Approaches

Others had mixed-methods designs of quantitative outcome measures and qualitative user feedback to determine both quality and experience aspects of AI interventions [28], [29]. Quantitative data involved the measures of loneliness and engagement, whereas the qualitative analysis was achieved by means of interviews and focus groups. Comparative study of cross-cultural differences in performance was conducted between age, geographical location, and culture. The results continuously showed that cultural norms and demographic variables had an impact on user acceptance, emotional response, and ethical concern, and culturally adaptive AI systems were required [30].

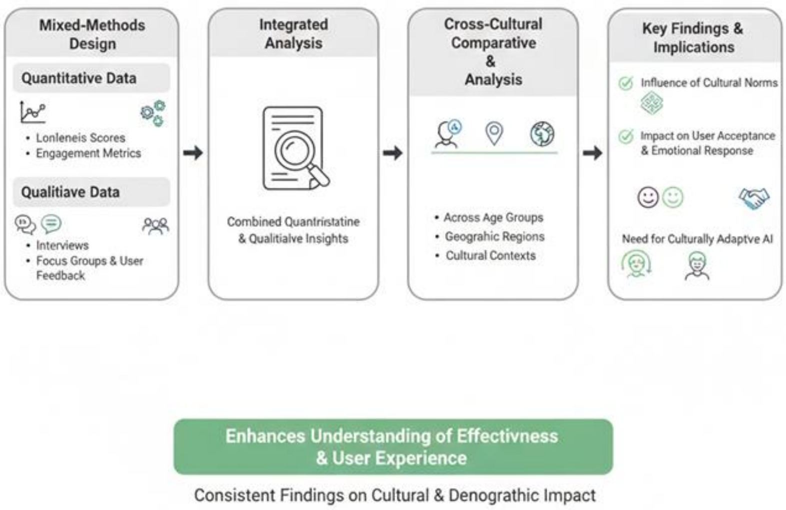

Fig. 6 User experience.

Comparison:- Comparison of the available options shows that chatbots and voice assistants are highly scalable and accessible, whereas social robots and multimodal emotion-sensitive systems prove to be more effective in reducing loneliness, especially among older users and those more interested in engagement.

Table 2: Comparative Analysis of AI Approaches for Loneliness Reduction.

Approach	Strengths	Effectiveness	Best For
Chatbots	High scalability, easy deployment	Consistent short-term improvements	Diverse populations
Social Robots	Stronger loneliness reduction	High, esp. older adults (RCTs)	Older adults
Voice Assistants	Accessible for homebound	Reduces perceived isolation	Homebound users
Hybrid Human-AI	Reduces dependency risks	Balanced, sustainable outcomes	Long-term use
Multimodal/Emotion AI	Outperforms text-only	Superior emotional detection	Engagement-focused
Explainable AI (XAI)	Enhances trust/clinical use	Improves usability	Clinical settings

RESULT AND ANALYSIS

The analysis of this study involved thirteen studies. The best evidence was found in the RCTs and meta-analyses, which reported an average reduction of 30-40 percent in the loneliness scores after the use of AI-based interventions. Qualitative research noted that user perceptions were positive and especially in chatbots and hybrid AI systems, they found positive effects in areas of empathy, accessibility, and engagement. A wide range of heterogeneity was perceived among the studies in the quality of design and duration, but lengthy and longitudinal studies proved their long-term sustainability. All in all, the results indicate that AI interventions can be effective in alleviating loneliness, and the positive effects are associated with the use of interventions in the long term.

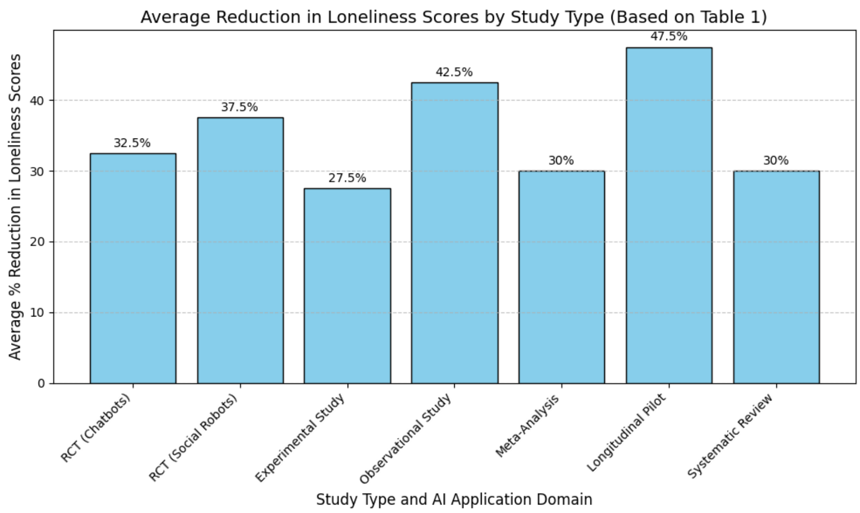

Fig. 7 Average reduction in loneliness scores by study type.

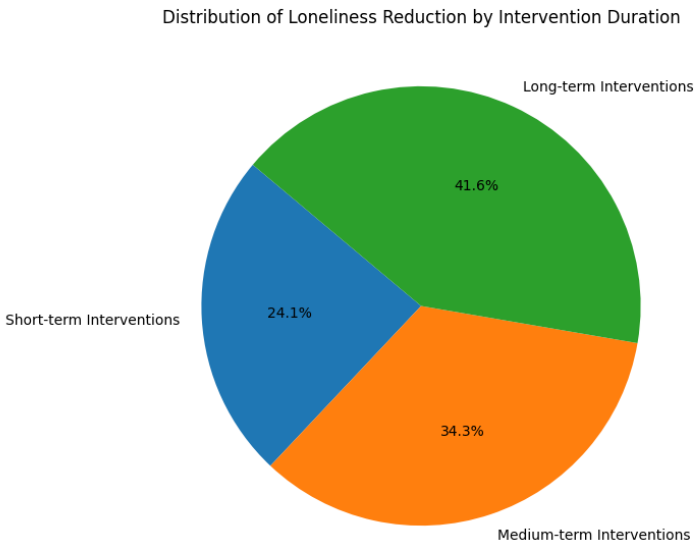

Fig. 8 Distribution of loneliness reduction by intervention duration.

CONCLUSION

The findings of this study suggest that AI-based interventions can help reduce loneliness effectively. Strong evidence from clinical trials and meta-analyses shows that loneliness levels decreased by about 30–40% after using AI interventions. Users also reported positive experiences, especially with chatbots and hybrid AI systems, which were found to be empathetic, accessible, and engaging. Although the included studies differed in design and duration, longer-term studies showed more stable and lasting results. Overall, this study indicates that AI interventions have the potential to provide long-term support in reducing loneliness.

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