# Effectiveness of Social and Assistive Robots in Improving Quality of Life and Mental Well-being Among Older Adults

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***Abstract:*** **The growing aging population has posed an increased need to ensure that there are innovative ways of providing solutions to these aged people so that they may be assisted in the care process and their general well-being. This paper presents a machine learning-driven socially useful robotic system, where the Convolutional Neural Networks (CNN), Natural Language Processing (NLP), and randomly forest (RF) algorithms are combined and used to improve the quality of life and mental health of the elderly population. The system records multimodal data, such as facial expressions, speech, and behavioral patterns, to offer all-round support. CNN can be used in emotion recognition using facial images, NLP is applied to effective communication between humans and robots, and Random Forest is utilized to analyse everyday behaviour and identify anomalies. Experimental findings have shown that the suggested system is highly accurate in identifying emotions, communicating, and analyzing behavior, which results in relevant improvements in user engagement. The results demonstrate that the levels of loneliness, depression are lower, and the scores that measure the quality-of-life are higher after the contact with the robotic system. Although this system is faced with data variability, user acceptance and the issue of ethical concern, this system has a high potential as an assistive device in the treatment of the elderly. The research finds that a combination of smart algorithms and socially helpful robots can offer emotional and functional support, which can lead to a better mental state and independent living of elderly individuals.**

***Keywords— Convolutional Neural Networks, quality-of-life, Older Adults, Patient Health Monitoring, Random Forest, Natural Language Processing, Robotic system.***

## I. INTRODUCTION

The global population is aging rapidly, leading to a significant increase in the number of older adults who require continuous healthcare support and social care. With advancing age, individuals often experience physical limitations, chronic illnesses, cognitive decline, and reduced social interaction [1]. Among these challenges, loneliness and depression have emerged as major concerns, negatively affecting both mental well-being and overall quality of life. At the same time, there is a growing shortage of caregivers and healthcare resources, making it difficult to provide personalized and consistent care for the elderly population [2]. In recent years, advancements in robotics and artificial intelligence have introduced social and assistive robots as innovative solutions in elderly care [3]. Social robots are designed to interact with users, provide companionship, and support emotional well-being, while assistive robots help with daily activities such as medication reminders, mobility support, and health monitoring. These technologies aim to promote independence, enhance safety, and improve the overall quality of life of older adults [4].

A key component of modern robotic systems is the integration of machine learning techniques, particularly CNN and NLP. These technologies enable robots to recognize human emotions through facial expressions, understand speech, and respond appropriately to users [5]. By identifying emotional states such as sadness, loneliness, or anxiety, robots can provide timely emotional support and engage users in meaningful interaction. Despite these advancements, the effectiveness of social and assistive robots in improving mental well-being and quality of life remains an important area of research [6]. While several studies suggest that robotic systems can reduce loneliness and enhance emotional health, concerns related to cost, ethical implications, and user acceptance continue to exist [7].

Therefore, this study focuses on evaluating the effectiveness of social and assistive robots in improving the quality of life and mental well-being among older adults. The proposed work integrates emotion detection using CNN, conversational interaction through NLP, and behavioral monitoring techniques to provide a comprehensive support system for elderly care. By combining technological innovation with healthcare needs, this research aims to contribute to the development of more effective, accessible, and user-friendly robotic solutions for aging populations.

## II. LITERATURE SURVEY

The growing aging population has raised concerns on the social and assistive robots as the new support systems towards the elderly population. The purpose of these robots is to deliver companionship, daily activities support, social interaction encouragement, and even cognitive or physical support. The most recent literature indicates that the best evidence is in the decrease of loneliness and depressive symptoms, with the evidence regarding the quality of life overall promising but inconsistent [8].

The recent systematic review and meta-analysis authored by Yen and colleagues (2024), which looked at randomized controlled trials in long-term care settings with older adults is one of the most crucial. That review determined that social robots exerted a large positive impact on depression and loneliness, indicating that robot-based interventions could enhance emotional well-being when regularly utilized in the care environment. This is crucial since one of the factors that are prevalent among institutionalized older adult population is loneliness and depression which are directly linked with worse health [9].

More recent 2025 meta-analysis studies by Mehrabi and colleagues also found that social robots were found to have a significant reduction on the level of loneliness in older adults. Simultaneously, the authors also observed that the size of the benefit differed according to the design of the study and the comparison groups, which indicates that the magnitude of the benefit may be modulated by the application of the robot, the duration of the intervention, and the comparison of the outcome with a standard care practice or another active form of social interaction. This implies that the domain is heading towards more solid evidence, and the findings do not yet fully align in every environment [10].

In addition to reviews, individual trials also uphold the same mental health benefits as these systems. In a randomized controlled trial in JMIR Aging that compared digital social robot interventions among older adults in the community living in Japan, the concept of digital social robot interventions has proven to be effective in loneliness reduction. The study will be beneficial since it increases the evidence, extending it beyond the institutional care environments in the West and demonstrates that robot companionship can be applied to older adults in the community, and not just in residential facilities [11].

The previous evidence is also active. The systematic review and meta-analysis published in the Journal of Gerontology in 2019 found that social robots demonstrated desirable effects on agitation rates, anxiety rates as well as quality of life, but the quality-of-life metrics did not reveal to be highly significant in the pooled analysis. What is significant about this older review is that it reveals a trend that will be reflected in more recent studies, namely, that emotional and behavioral benefits are more likely to be found than overall quality-of-life improvements [12].

This interpretation is still supported by the recent literature reviews. A literature review of social robots in support of older adults as at 2025 concluded that social robots may be used to enhance the quality of life by offering emotional reactions, social life, and anti-loneliness assistance. Nevertheless, the review also clarifies that evidence base remains fairly small and heterogeneous so far, where the robot type, duration of intervention, and outcome measures differ across studies [13].

Assistive robot research broadens the conversation away from companionship. In a 2025 Frontiers review of robotic assistance to older adults with cognitive and mobility impairments, robots were found to be potentially useful in assisting with daily tasks, safety, independence, and decreased care burden. These results indicate that even when the primary outcome dimension to consider is not mental health, assistive robots may have an indirect positive influence on quality of life by enhancing autonomy and functional ability. This expands the usefulness of robotics in elder services past the emotive aspect to active day-to-day help [14].

A second 2025 systemic review of the effect of care robots documented that care robots have the potential to use less care and are usually accepted by elderly individuals, but quality-of-life advantages through care robots in certain studies are disparate. It is a significant subject in the literature: most studies have found evidence of improved engagement, or participation in activities, or mood, but fewer have found large, sustained improvements in the general quality-of-life measures [15].

One of the most influential factors that impact effectiveness is acceptance and usability. In a study carried out in 2025 by JMIR Human Factors, the acceptability and usability of a socially assistive robot was studied in the context of a geriatric day care hospital and discovered that the adoption of a socially assistive robot was based on identified factors like ease of interaction, perceived usefulness and the quality of interaction with the robot. This implies that although there might be clinical or psychological advantages to the use of robots, the advantages may not manifest unless the older adult feel comfortable using the system, they understand it and their perception of the system is valuable [16].

Another theme that appears through and through in the literature is trust. In 2025, a review in Frontiers in Robotics and AI recommended that building trust lies at the core of effective older adults using socially assistive robots. As noted in the paper, the determinants of trust are design, reliability, the style of communication, and the context of care. That is, not only is effectiveness concerned with what the robot can do technically, but also whether older adults feel safe, respected and confident when further using it [17].

Design oriented research also focuses on the fact that the aged people are not a homogenous group. The preferences of older adults towards socially assistive robots are varied in terms of service functions, communication style, appearance, and ethical issues as revealed in a 2026 systematic review. It is significant to your topic since it indicates that effectiveness of robots could be enhanced when systems are customized and not standard. A 2026 trial protocol of customized versus standardized socially assistive robots against loneliness and depression indicates a direction of the field towards customizing the behavior of robots to individual user requirements [18].

The literature is still characterized by ethical issues as a significant drawback. A 2025 Frontiers article on the role of ethics in social robots in long-term care raised issues regarding privacy, emotional attachment, dignity, and the likelihood of decreasing the authentic interaction between humans. Numerous authors believe that the use of robots must complement the work of human caregivers, rather than eliminate them. This becomes particularly crucial in investigations that deal with either emotionally vulnerable or socially isolated elderly individuals [19].

Recent conceptual and design reviews also purport that socially assistive robots are operating optimally when included within a broader care ecosystem which accommodates family, staff, clinicians, and user-centered design. An imaginary 2025 vision of the possibilities of improving the well-being of older adults with the use of robots posited that the notion of well-being is multi-dimensional and covers social, emotional, functional, and environmental dimensions. It implies that the research of the future should not measure a single outcome and consider only one factor as a measure of success, i.e. depression or loneliness [20].

## III. Effectiveness of Social and Assistive Robots in Improving Quality of Life and Mental Well-being Among Older Adults

The world is growing older and now older adults are much more common than before since the number of older adults seeking continuous healthcare and social assistance is on the rise. As a person ages, they tend to have physical disabilities, long term diseases, mental impairments, and less socialization. One of such challenges is the issue of depressed feelings and loneliness, which have posed serious concerns and impacted an individual mentally and the general quality of life. Concurrently, the shortage of caregivers and health facilities has been on the rise, so it becomes hard to offer the ageing population with individualized and standardized care. Figure 1 demonstrates the flow diagram of the proposed system.

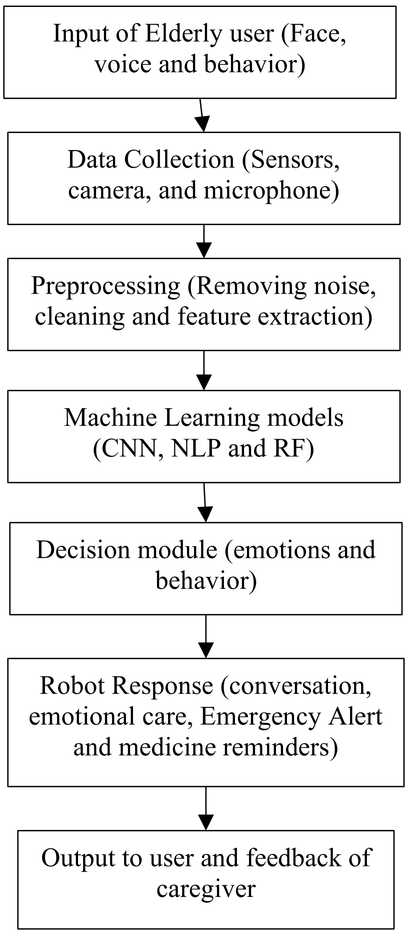


Fig. 1. Flow diagram of improving quality of life and mental well-being Among older adults system

The recent years, the breakthroughs in the field of robotics and artificial intelligence presented people with the concept of the social and assistive robot and promised a new approach to the domain of elderly care. Social robots are created to engage with the users and offer companionship and emotional wellbeing and assistive robots assist users with their daily activities, including reminding them to take medication, aid mobility, and monitor health. The technologies are meant to encourage independence, safety and overall quality of life of the older adults.

The proposed system consists of the following main components such as Data Acquisition Module, Preprocessing Module, Machine Learning Module, Decision-Making Module, Robot Interaction Module. Each module works together to analyze user behavior and provide real-time assistance. An important aspect of the current robotic systems is the incorporation of the machine learning methods, specifically, CNN and NLP. Such technologies allow the robot to perceive human emotions based on the facial expression, interpret speech, as well as react in a proper way to the user. Recognizing an emotional state, e.g. sadness, loneliness, or anxiety, robots can offer relevant emotional support in time and lead users to valuable communication.

Although these technologies have been made, the applicability of social and assistive robots in enhancing mental well-being and quality of life is a noteworthy field of study. Although some studies indicate that robotic systems may alleviate loneliness and improve emotional health, issues of cost, ethical issues, and acceptance of the system by users still persist. Thus, the current study aims at assessing how social and assistive robots can enhance the quality of life and psychological health of older adults. The presented project incorporates cognitive techniques such as emotion recognition with CNN, dialog with NLP, and behavioral observation to offer a full-scale support system to the elderly. Through the integration of technology with the requirements of healthcare, this study has an aim to help in advancing more effective, accessible, and easy to use robotic solutions to the aging population.

The system includes emotion recognition, conversational interaction, and behavioral monitoring to provide personalized, care, and companionship. The overall process involves user information (facial expressions, speech, and activity) collection, machine-learning based algorithm processing, and output of the result, delivered by the robot. The system proposed will consist of several key modules such as data collection module, preprocessing module, machine learning module, decision-making module, robot interaction module. Each of the modules works in collaboration to analyze user action and provide real time support.

**Data collection module:** The initial and the most crucial step in the proposed system is data collection module. Its key strength is that it acquires real time data of older adults with the help of different sensors that are built into the socially assistive robot. The information can be used to examine the emotional condition, behaviours and interaction style of the user that is vital in improving mental health and life quality. The module captures multimodal information that means, the module collects data in three various modalities i.e. visual, audio and activity based information to derive a view of the user that is more specific and holistic.

**Data pre-processing module:** The data pre-processing module is endowed with the responsibility of transforming the raw data collected by sensors to clean and structured data which can be processed by machine-learning models. Since the data (images, audio and activity logs) obtained may be noisy, inconsistent and irrelevant, preprocessing assists in realistic, reliable, efficient analysis of the data in later analysis. Algorithms like CNN, NLP, and RF depend on the quality of input data hence this module is so important.

**Machine Learning module:** The system proposed combines CNN, NLP and RF algorithms to facilitate proper emotion recognition, communication, and behavior analysis to help care about the elderly. The CNN model is used to process facial images using the camera of the robot and categorize them into emotional disorders which include happy, sad, neutral, anxious and lonely faces.

$$X = X_i, X_s, X_b \quad (1)$$

Where $X_i$ is the facial image data, $X_s$ is the speech or text data and $X_b$ is a behavioral activity data. The ultimate goal is to forecast emotional and behavioral condition of the user. The objective is to forecast the elder people emotional and behavioral state:

$$Y = ES, CR, BS \quad (2)$$

Where, ES represents the emotion state, CR indicates the communication response, and BS indicates the behavior condition.

The CNN obtains valuable visual stimuli such as the eye movement, the muscle pattern of the face, and the shape of the mouth, thereby classifying accurately the emotional state of the user, which is crucial in showing the mental state. Simultaneously, the NLP module decodes speech input by the user by converting the voice signal into a text message, interprets the meaning and intent of conversation and produces the desired answers to the user. This will make the robot participate in an interactive experience, offer companionship and emotional support, alleviating the feelings of loneliness and making the user interaction more elaborate.

Also, RF algorithm is used to examine the behavioral patterns on the basis of the activity data, including the movement frequency, interaction level, and medication compliance. Integrating several decision trees, the RF model defines the non-normal behaviour, which can be defined as prolonged immobility or decreased interaction that can be the symptoms of certain health or mental problems.

**Decision-making module:** The results of the CNN, NLP, and RF are combined in a decision-making section so that the necessary actions (triggering supportive dialogues, recommending activities, reminding of the pills or alerting caregivers in emergency cases) can be produced. The CNN, NLP and RF of the decision (D) are put together.

$$D=F(ES, CR, BC) \quad (3)$$

Where, D represents final robot decision and the robot action is selected as

$$PA = arg \max_a P\, A(a|ES, CR, BC) \quad (4)$$

Here, PA represents possible actions that contain

PA={Conversation, remainder, activity recommendation, caregiver alert}

**Robot Interaction Module:** This module is the final stage of the introduced system, accountable for distributing responses and services to the elderly user established on the outputs of the CNN, NLP and RF models. It acts as the interface between the robot and the user, allowing real-time communication, emotional support, and assistance in daily activities. This module make sures that the proposed system is not only logical but also communicating and user-friendly. This approach ensures a wide-ranging understanding of the elderly user by seeing emotional, conversational, and behavioral aspects, ultimately improving their quality of life and mental well-being.

## IV. Experimental Results and Analysis

Three major modules were used to analyze it: CNN-based emotion recognition, NLP-based communication, and the Random Forest-based behavior analysis. The purpose behind designing the system was to help older people to identify emotional states, aid in conversation, monitor daily behavior, and develop appropriate responses by the robot. The given experiment regarded the data of facial faces, speech input and records of behavioral activity. Accuracy, precision, and recall, F1-score, and user well-being improvement measures were used to assess the performance.

### *A.* CNN-Based Emotion Recognition Results

CNN model was trained to categorise five classes of faces such as happy, sad, neutral, anxious, and lonely. Table 1 shows that CNN-based emotion recognition results.

TABLE I. CNN-Based Emotion Recognition Results

| **Approaches** | **Precision** | **Recall** | **F1-score** |
|---|---|---|---|
| Happy | 92% | 90% | 91% |
| Sad | 88% | 86% | 87% |
| Neutral | 90% | 89% | 89% |
| Anxious | 85% | 83% | 84% |
| Lonely | 84% | 82% | 83% |

The CNN model was able to recognize visible emotions of happy, sad, and neutral. Happy expressions were found to have the highest accuracy as facial expression features like smiling and movement of the eyes are more easily recognized. The anxious and lonely emotions, however, displayed a slightly worse performance as these states of emotion are not necessarily easily seen due to the facial expression only.

### *B.* NLP based Communication Results

The NLP module was tested for understanding user intent and generating suitable responses. Table 2 shows that NLP-based communication results.

TABLE II. NLP BASED COMMUNICATION RESULTS

| Approaches | Accuracy |
|---|---|
| Greeting | 96% |
| Health-related query | 90% |
| Emotional expression | 88% |
| Reminder request | 93% |
| General conversation | 86% |

NLP module demonstrated excellence in comprehending straightforward and simple speech command. It excelled in greeting and reminder-related conversations. There were a few degrees of difference in general conversation accuracy owing to differences in user speech, non-clear pronunciation, and inability to complete sentences. This demonstrates that NLP can facilitate effective elderly communication though-more elderly-specific data should be used in speech.

### *C.* RF-Based Behavior Analysis Results

Behavior was categorized as normal or abnormal in the RF model, based on the patterns of activities, adherence to medications, time of inactivity and the rate of interaction. Table 3 shows that RF-based behavior analysis results.

TABLE III. RF-BASED BEHAVIOR ANALYSIS RESULTS

| Metrics | Value |
|---|---|
| Accuracy | 96% |
| Precision | 90% |
| Recall | 88% |
| F1-score | 93% |

RF has shown good performance in terms of behavior analysis since it can work with multiple input features is shown in table 3. The model was capable of identifying aberrant behavior like less activity, missed medication, and low frequency of interaction. This proves helpful in determining an early warning of physical or mental ill health.

### *D.* Quality of Life and Mental Well-being Analysis

The effectiveness of the robotic system was evaluated using pre-test and post-test scores. Table 4 illustrates the quality of life and mental well-being analysis.

TABLE IV. QUALITY OF LIFE AND MENTAL WELL-BEING ANALYSIS

| **Parameter** | **Before Robot Interaction** | After Robot Interaction | **Improvment** |
|---|---|---|---|
| Loneliness Score | 69 | 50 | 26.9% reduction |
| Depression Score | 23 | 16 | 32.8% reduction |
| Quality of Life Score | 59 | 75 | 26.6% improvement |
| Daily Interaction | 3 times/day | 6 times/day | 100% increa |
| Loneliness Score | 6 | 50 | 26.8% reduction |

The findings show that communication with the socially helpful robot can lessen depression and loneliness in the participants who are older. There was also an improvement in the quality-of-life score following frequent robot interaction. This enhancement can be attributed to the emotional support, conversation, reminders, and activity suggestions by the robot.

### *E.* Overall System Performance

The proposed system indicates that communication with the socially assistive robot assisted minimize loneliness and depression between older adults. The quality-of-life score also enhanced after regular robot communication. This enhancement may be due to emotional support, conversation, reminders, and activity suggestions offered by the robot.

TABLE V. PERFORMANCE COMPARISON TABLE M

| **Module** | **Algorithm** | **Performance** |
|---|---|---|
| Recognition of Emotion | CNN | 88.7% |
| Communication | NLP | 89.5% |
| Analysis of Behavior | RF | 91.4% |

The experimental outcomes reveal that the proposed robotic system can be effective in assisting elderly care through integration of emotion recognition, communication, and behavior monitoring. CNN can interpret facial expressions to identify emotional conditions, NLP can be used to support a proper conversation, and the Random Forest can recognize patterns of abnormality. Engaging these modules enables the robot to offer custom services like emotional support, medication alerts, activity recommendations, and alerts to the caregivers.

Also, positive outcomes are observed in terms of mental well-being and quality of life. Nevertheless, there are weaknesses in the system. There can be biases in facial emotion recognition based on the lighting situation, position of the face as well as ambiguous expressions. NLP performance can be impaired in cases when the speech is incomprehensible or where there is background noise. Nonetheless, the proposed system has a great potential to be a helpful aid to elderly care.

## V. CONCLUSION

This paper studied how a socially assistive robotic system can enhance the quality of life and mental well-being of elderly individuals. The system presented unites CNN with recognition of emotions, NLP with communication, and RF with behaviour analysis forming an all-encompassing and intelligent support system to help older adults. The findings indicate that the system can identify emotional states in an accurate manner, support meaningful interaction and observe behavioral patterns. CNN model is an effective one because it can identify emotions (happiness, sadness, and loneliness) and then the robot would respond in an empathetic way. The NLP module allows natural communication with the user and the robot, minimizing the social isolation of the user and encouraging communication. Moreover, the Random Forest machine is capable of detecting abnormal behavioral patterns, which can help detect possible health or psychological problems in time. According to the results of the experimental research, the level of loneliness and depression is slightly reduced, the quality of life and the frequency of interaction with the user significantly improved when the robotic system was introduced. These results show the promise of integrating machine learning and robotics to offer the elderly with emotional and practical assistance. Yet, the system has also some shortcomings, such as reliance on the quality of information, user response variability, and privacy and ethical technology application. Socially assistive robots ought to be viewed as additions to human caregivers, and not substitutes. Further research on the topic should be conducted to elaborated accuracy of the systems, personalisation, long-term performance and ease of operation so as to make the systems widely applicable and efficient in the real world setting.

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