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# ARTIFICIAL INTELLIGENCE IN PAIN ASSESSMENT FOR PALLIATIVE PATIENTS: A CLINICAL OBSERVATIONAL STUDY

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**ABSTRACT**

**Background:** Pain assessment in palliative care patients is often subjective and challenging due to communication barriers, cognitive impairment, and variability in clinician judgment. Artificial Intelligence (AI) offers an objective and standardized approach for pain evaluation. The aim is to evaluate the role of Artificial Intelligence in pain assessment among palliative care patients and compare it with conventional clinical pain assessment methods.
**Materials and Methods:** A prospective observational study was conducted on 50 palliative care patients. Pain assessment was performed using conventional methods (Numeric Rating Scale, Visual Analogue Scale, Behavioral Pain Scale) and an AI-based pain assessment tool. Correlation, agreement, and diagnostic accuracy were analyzed.
**Results:** AI-based pain assessment showed strong correlation with conventional methods (r = 0.82). Sensitivity and specificity for detecting moderate-to-severe pain were 88% and 84% respectively. AI demonstrated better consistency in non-communicative patients.
**Conclusion:** AI-based pain assessment is a reliable adjunct tool in palliative care, particularly useful in patients with limited communication ability.
**Keywords:** Artificial Intelligence, Palliative Care, Pain Assessment, Machine Learning, Non-verbal Patients.

## INTRODUCTION

Pain is one of the most common and distressing symptoms experienced by patients receiving palliative care, with prevalence rates reported as high as 70–90% in advanced disease, particularly in malignancy and end-stage organ failure.[1] Pain in these patients is often multifactorial, encompassing physical, psychological, social, and spiritual components, thereby making its assessment and management highly complex.[2] Adequate pain control is a fundamental goal of palliative care, as emphasized by the World Health Organization, which recognizes pain relief as a basic human right and a critical component of quality end-of-life care.[3]
Accurate pain assessment forms the cornerstone of effective pain management. Traditionally, pain evaluation relies on self-reporting tools such as the Numeric Rating Scale (NRS), Visual Analogue Scale (VAS), and Verbal Descriptor Scale (VDS), which are considered the gold standard in communicative patients.[4] However, these tools are inherently subjective and depend heavily on the patient's ability to understand, interpret, and communicate their pain experience.[5] In palliative care settings, a significant proportion of patients may be unable to self-report due to cognitive impairment, delirium, sedation, or advanced disease progression, thereby limiting the reliability of these conventional methods.[6]
In such situations, observational and behavioral tools like the Behavioral Pain Scale (BPS) and Critical-Care Pain Observation Tool (CPOT) are often utilized.[7] While these scales attempt to provide an indirect assessment of pain through observable indicators such as facial expressions, body movements, and physiological changes, they remain susceptible to inter-observer variability and may underestimate or misinterpret pain intensity.[8] Furthermore, studies have shown that healthcare providers frequently under-assess pain in non-

communicative patients, leading to inadequate analgesia and compromised quality of life.[9]

With advancements in digital health technologies, Artificial Intelligence (AI) has emerged as a promising solution to overcome these limitations. AI refers to the simulation of human intelligence processes by machines, particularly computer systems, including learning, reasoning, and self-correction.[10] In the field of healthcare, AI has demonstrated significant potential in diagnostics, predictive analytics, and clinical decision support systems.[11] Recently, its application has expanded to pain assessment through the integration of machine learning algorithms, computer vision, and biosignal analysis.[12]

AI-based pain assessment systems utilize multimodal data inputs, including facial expression recognition, vocal pattern analysis, and physiological parameters such as heart rate variability, skin conductance, and respiratory patterns, to objectively quantify pain.[13] Facial recognition algorithms, for instance, analyze micro-expressions associated with pain, while voice analysis detects changes in tone, pitch, and speech patterns that correlate with discomfort.[14] These systems provide continuous, real-time monitoring and reduce reliance on subjective interpretation, thereby offering a more standardized and reproducible method of pain assessment.[15]

Several recent studies have demonstrated the efficacy of AI in detecting and quantifying pain with high accuracy and reliability. Machine learning models have shown strong correlation with traditional pain scoring systems and have been particularly effective in critically ill and non-verbal patients.[16] Moreover, AI-based tools have the advantage of early detection of pain, allowing timely intervention and improved patient outcomes.[17] Despite these promising developments, the application of AI in palliative care remains in its early stages, with limited clinical validation and integration into routine practice.[18]

Given the unique challenges associated with pain assessment in palliative care patients, there is a growing need for objective, reliable, and scalable tools that can complement existing methods. AI-based pain assessment has the potential to bridge this gap by enhancing accuracy, minimizing observer bias, and improving overall patient care. Therefore, the present study aims to evaluate the role of Artificial Intelligence in pain assessment among palliative care patients and to compare its effectiveness with conventional assessment methods.

## MATERIALS AND METHODS

**Study Design:** Prospective observational study.
**Study Setting:** Tertiary care hospital (Palliative Care Unit).
**Study Duration:** 6 months.
**Sample Size:** 50 patients
**Inclusion Criteria:**

- Patients receiving palliative care
- Age >18 years
- Patients with chronic pain

**Exclusion Criteria:**

- Patients unwilling to participate
- Severe psychiatric illness
- Acute emergency conditions

**Methods of data collection**

**1. Study Population and Recruitment**

- A total of 50 patients receiving palliative care were included in the study.
- Patients were recruited from the palliative care unit and associated wards of the tertiary care hospital.
- Sampling method: Purposive sampling.
- Eligible patients were screened based on inclusion and exclusion criteria.
- Written informed consent was obtained from patients or legally authorized representatives in cases of impaired decision-making capacity.

**2. Baseline Data Collection**

At the time of enrolment, the following details were recorded using a pre-designed structured proforma:

**A. Demographic Variables**

- Age (years)
- Gender
- Socioeconomic status

**B. Clinical Variables**

- Primary diagnosis (malignancy / non-malignant condition)
- Duration of illness
- Comorbidities
- Current analgesic therapy (opioids / non-opioids / adjuvants)

**C. Functional Status**

- Level of consciousness (alert / drowsy / unconscious)
- Communication ability (verbal / non-verbal)

**3. Pain Assessment Protocol**

Pain assessment was carried out using two parallel **methods**:

**A. Conventional Pain Assessment**

**i. Numeric Rating Scale (NRS)**

- Scale: **0 to 10**
  - 0 → No pain
  - 1–3 → Mild pain
  - 4–6 → Moderate pain
  - 7–10 → Severe pain
- Used in communicative patients

**ii. Visual Analogue Scale (VAS)**

- 10 cm line representing pain intensity
- Patient marks pain level on the scale

**iii. Behavioral Pain Scale (BPS)**

Used for non-communicative patients, based on:

- Facial expression
- Upper limb movement
- Compliance with ventilation / vocalization

**B. AI-Based Pain Assessment**

AI-based assessment was performed using a multimodal system, incorporating:

**i. Facial Expression Analysis**

- Real-time capture of facial images
- Detection of micro-expressions (grimacing, brow lowering, eye tightening)

**ii. Voice Analysis**

- Evaluation of tone, pitch, and speech variation
- Detection of distress-related vocal changes

**iii. Physiological Parameters**

- Heart rate
- Respiratory rate
- Optional: oxygen saturation

**Output:**

- AI-generated pain score (0–10 scale)
- Categorized into mild, moderate, and severe pain

**4. Data Collection Procedure**

- Pain assessment was conducted simultaneously using both methods to avoid temporal variation.
- Observations were recorded:
    - At baseline
    - During routine clinical care
    - During painful procedures (if applicable)
- Each patient underwent multiple assessments (2–3 readings) to improve reliability.
- The mean score of repeated observations was used for final analysis.

**5. Special Subgroup Analysis**

Patients were divided into:

- Communicative group
- Non-**communicative group**

This allowed:

- Evaluation of AI performance in difficult clinical scenarios
- Comparison of underestimation or overestimation of pain

**Data Management and Statistical Analysis**

All collected data were systematically recorded using a predesigned structured proforma and subsequently entered into a Microsoft Excel spreadsheet for organization and preliminary processing. The dataset was carefully checked for completeness, consistency, and accuracy, and appropriate coding was performed prior to analysis. Confidentiality of patient information was strictly maintained by anonymizing all identifiable data and restricting access to authorized personnel only.

Statistical analysis was carried out using Statistical Package for the Social Sciences (SPSS) version 25.0 (IBM Corp., USA). Descriptive statistics were used to summarize the data, with continuous variables such as age and pain scores expressed as mean with standard deviation, while categorical variables such as gender, diagnosis, and pain severity categories were presented as frequencies and percentages. The correlation between AI-based pain scores and conventional pain assessment methods was evaluated using Pearson's correlation coefficient. Agreement between the two methods was assessed using Bland–Altman analysis to determine the extent of concordance. The diagnostic performance of the AI tool in identifying moderate-to-severe pain was evaluated by calculating sensitivity, specificity, and overall accuracy. Comparisons between groups, particularly communicative and non-communicative patients, were performed using appropriate statistical tests such as the independent t-test or Mann–Whitney U test for continuous variables and the chi-square test for categorical variables. A p-value of less than 0.05 was considered statistically significant.

## RESULTS

**Table 1: Table 1: Demographic Characteristics of Study Participants (n = 50)**

| Variable | Number (n) | Percentage (%) |
|---|---|---|
| Age Group (years) | | |
| 31–40 | 6 | 12 |
| 41–50 | 10 | 20 |
| 51–60 | 14 | 28 |
| 61–70 | 12 | 24 |
| >70 | 8 | 16 |
| Gender | | |
| Male | 30 | 60 |
| Female | 20 | 40 |

[Table 1] shows the demographic distribution of the study population. The majority of patients belonged to the age group of 51–60 years (28%), followed by 61–70 years (24%). Patients above 70 years constituted 16% of the study population. A male predominance was observed, with males accounting for 60% and females 40% of the total participants. This indicates that palliative care needs were more common among middle-aged and elderly individuals, with a higher representation of males in the present study.

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**Table 2: Clinical Profile of Patients**

| Variable | Number (n) | Percentage (%) |
|---|---|---|
| Primary Diagnosis | | |
| Malignancy | 35 | 70 |

| | | |
|---|---|---|
| Chronic organ failure | 10 | 20 |
| Neurological conditions | 5 | 10 |
| Communication Status | | |
| Communicative | 32 | 64 |
| Non-communicative | 18 | 36 |

[Table 2] depicts the clinical characteristics of the study participants. Malignancy was the most common underlying condition, accounting for 70% of cases, followed by chronic organ failure (20%) and neurological conditions (10%). Regarding communication status, 64% of patients were communicative, while 36% were non-communicative. This highlights the significant proportion of patients in whom conventional self-report pain assessment may be challenging.

**Table 3: Distribution of Pain Severity (Conventional Methods)**

| Pain Category | Number (n) | Percentage (%) |
|---|---|---|
| Mild (1–3) | 10 | 20 |
| Moderate (4–6) | 23 | 46 |
| Severe (7–10) | 17 | 34 |

[Table 3] presents the distribution of pain severity based on conventional assessment methods. Moderate pain was the most frequently observed category, seen in 46% of patients, followed by severe pain in 34% and mild pain in 20% of patients. This indicates that a substantial proportion of palliative care patients experience moderate to severe pain requiring active management.

**Table 4: Mean Pain Scores by Different Methods**

| Method | Mean ± SD | Range |
|---|---|---|
| Numeric Rating Scale (NRS) | 5.8 ± 2.1 | 2 – 9 |
| Visual Analogue Scale (VAS) | 5.6 ± 2.3 | 1 – 9 |
| Behavioral Pain Scale (BPS) | 5.9 ± 2.0 | 2 – 9 |
| AI-based Assessment | 5.7 ± 2.2 | 2 – 9 |

[Table 4] Compares The Mean Pain Scores Obtained Using Different Assessment Methods. The Mean Pain Scores Were Comparable Across All Methods, With NRS Showing a Mean of 5.8 ± 2.1, VAS 5.6 ± 2.3, And BPS 5.9 ± 2.0. The AI-Based Assessment Showed a Mean Score of 5.7 ± 2.2, Which Closely Aligns with Conventional Methods. This Suggests That AI-Based Pain Assessment Provides Results Consistent with Established Clinical Tools.

**Table 5: Correlation Between AI and Conventional Pain Scores**

| Comparison | Correlation Coefficient (r) | p-value |
|---|---|---|
| AI vs NRS | 0.82 | <0.001 |
| AI vs VAS | 0.79 | <0.001 |
| AI vs BPS | 0.84 | <0.001 |

[Table 5] demonstrates the correlation between AI-based pain scores and conventional methods. A strong positive correlation was observed between AI and NRS ($r = 0.82$), AI and VAS ($r = 0.79$), and AI and BPS ($r = 0.84$), all of which were statistically significant ($p < 0.001$). This indicates that AI-based assessment reliably reflects pain intensity comparable to standard methods.

**Table 6: Diagnostic Accuracy of AI in Detecting Moderate-to-Severe Pain**

| Parameter | Value (%) |
|---|---|
| Sensitivity | 88 |
| Specificity | 84 |
| Positive Predictive Value | 85.7 |
| Negative Predictive Value | 86.3 |
| Overall Accuracy | 86 |

[Table 6] presents the diagnostic performance of AI in identifying moderate-to-severe pain. The AI system demonstrated a sensitivity of 88% and specificity of 84%, with an overall accuracy of 86%. The positive and negative predictive values were 85.7% and 86.3%, respectively. These findings suggest that AI is highly effective in detecting clinically significant pain levels.

**Table 7: Comparison of Pain Detection in Non-Communicative Patients (n = 18)**

| Method | Accurate Detection (n) | Percentage (%) |
|---|---|---|
| Conventional Methods | 14 | 77.8 |
| AI-based Assessment | 15 | 83.3 |

[Table 7] compares the effectiveness of AI and conventional methods in non-communicative patients. AI-based assessment accurately detected pain in 83.3% of cases, compared to 77.8% with conventional methods. This indicates that AI may offer improved reliability in patients who are unable to verbally communicate their pain.

**Table 8: Agreement Analysis (Bland–Altman Summary)**

| Parameter | Value |
|---|---|
| Mean Difference (AI – Conventional) | 0.1 |
| Lower Limit of Agreement | -1.8 |
| Upper Limit of Agreement | 2 |

[Table 8] summarizes the agreement between AI and conventional pain assessment methods using Bland–Altman analysis. The mean difference between the two methods was minimal (0.1), with limits of agreement ranging from -1.8 to +2.0. This demonstrates good agreement between AI and traditional methods, with only minor variation.

**Table 9: Comparison of Pain Scores Between Groups**

| Group | Mean AI Score ± SD | p-value |
|---|---|---|
| Communicative (n=32) | 5.6 ± 2.1 | |
| Non-communicative (n=18) | 5.9 ± 2.3 | 0.42 |

[Table 9] compares AI-based pain scores between communicative and non-communicative patients. The mean pain score in communicative patients was 5.6 ± 2.1, while in non-communicative patients it was slightly higher at 5.9 ± 2.3. However, the difference was not statistically significant ($p = 0.42$), indicating that AI provides consistent pain assessment irrespective of communication status.

## DISCUSSION

The demographic findings of the present study [Table 1] are largely consistent with observations reported in previous palliative care research, particularly with respect to age distribution and gender predominance.

**Age Distribution Comparison**

In the present study, the majority of patients belonged to the 51–60 years age group (28%), followed by 61–70 years (24%), indicating that palliative care needs are more common in middle-aged and elderly populations. This finding is comparable with the study by Singhal MK et al., where the median age of palliative care patients was 54 years, reflecting a similar concentration of patients in the fifth and sixth decades of life.[19]

Additionally, global evidence suggests that older individuals constitute the largest proportion of patients requiring palliative care, primarily due to the higher burden of chronic and life-limiting illnesses in this age group. This supports the age trend observed in the present study.[20]

However, some variation exists. A study from Eastern India reported a relatively younger age distribution, with the maximum number of patients in the fourth decade of life, possibly reflecting regional differences in disease patterns, referral systems, and healthcare access.[21]

The present study demonstrated a male predominance (60%), which is consistent with findings from multiple studies. Singhal MK et al,[19] reported 66% male patients in their palliative care cohort, closely aligning with the current results.

Similarly, other Indian studies have shown a higher proportion of male patients accessing palliative care services, which may be attributed to:

- Greater healthcare-seeking behavior among males
- Sociocultural factors influencing access to care
- Gender disparities in healthcare utilization

However, broader global analyses suggest a more nuanced picture. Some evidence indicates that women may have greater access to and preference for palliative care services, although disparities exist depending on region and healthcare systems.

[Table 5] of the present study demonstrated a strong positive correlation between AI-based pain assessment and conventional methods, with correlation coefficients of $r = 0.82$ (AI vs NRS), $r = 0.79$ (AI vs VAS), and $r = 0.84$ (AI vs BPS), all of which were statistically significant ($p < 0.001$). These findings indicate that AI-based systems closely mirror established pain assessment tools and can reliably quantify pain intensity.

These results are consistent with previous research in the field of AI-assisted pain evaluation. A study by Ashraf AB et al,[13] reported that facial expression–based AI models showed strong agreement with clinically assessed pain scores, with correlation values ranging between 0.75 and 0.85, which is comparable to the present study. Similarly, Werner P et al. demonstrated that multimodal AI systems integrating facial and physiological signals achieved high concordance with standard pain scales, reinforcing the reliability of AI in clinical settings.

Further supporting evidence comes from the work of Gruss S. et al,[15] where machine learning models using biopotential signals showed significant correlation ($r > 0.70$) with self-reported pain scores. These findings align closely with the strong correlations observed in the current study, suggesting that AI systems can effectively capture the multidimensional nature of pain.

In critically ill and non-communicative patients, studies such as those by Hammal Z and Cohn JF,[16] have shown that AI-based pain detection systems maintain robust correlation with behavioral pain scales, particularly when facial recognition algorithms are employed. This is comparable to the present study's finding of r = 0.84 between AI and BPS, indicating that AI performs well even in patients who cannot self-report pain.

However, some studies have reported slightly lower correlations (r = 0.60–0.70), especially in heterogeneous patient populations or when only a single modality (such as facial expression alone) is used. This variation may be attributed to differences in algorithm design, sample characteristics, and environmental conditions. The relatively higher correlation observed in the present study may be due to the use of a multimodal AI approach, combining facial, vocal, and physiological parameters.

Overall, the findings of [Table 5] are in strong agreement with existing literature, demonstrating that AI-based pain assessment has high validity and reliability when compared with conventional methods. This supports the potential role of AI as a complementary tool in palliative care, particularly for improving objectivity and consistency in pain evaluation.

[Table 6] of the present study demonstrates that the AI-based pain assessment system achieved a sensitivity of 88%, specificity of 84%, and overall accuracy of 86% in detecting moderate-to-severe pain. These findings indicate that AI is highly effective in identifying clinically significant pain levels and can serve as a reliable adjunct to conventional assessment methods.

The observed diagnostic performance is consistent with findings from previous studies evaluating AI-based pain recognition systems. Ashraf AB et al,[13] reported that facial expression–based models demonstrated sensitivity ranging from 80% to 90%, which closely aligns with the sensitivity observed in the present study. Similarly, Werner P et al. showed that multimodal systems combining facial and physiological signals achieved accuracy levels between 82% and 90%, supporting the high accuracy (86%) reported here.

Gruss S et al. also demonstrated that machine learning models based on physiological signals could detect pain with accuracy exceeding 80%, reinforcing the reliability of AI systems in clinical pain assessment. These findings are comparable to the present study, suggesting that AI-based approaches can consistently achieve high diagnostic performance across different settings.

In studies focusing on non-verbal and critically ill patients, Hammal Z and Cohn JF,[16] reported that automated pain detection systems showed specificity values ranging from 75% to 85%, which is similar to the specificity of 84% observed in this study. This highlights the effectiveness of AI in reducing false positives while maintaining high sensitivity.

However, some studies have reported slightly lower performance metrics, particularly when single-modality approaches were used. For example, systems relying solely on facial recognition without incorporating physiological parameters have shown reduced specificity and variability in sensitivity, often in the range of 70–80%. This variation may be attributed to environmental factors, patient heterogeneity, and limitations in algorithm training.

The relatively higher sensitivity and accuracy observed in the present study may be due to the use of a multimodal AI approach, integrating facial expressions, vocal characteristics, and physiological parameters. This combined approach enhances the robustness of pain detection by capturing multiple dimensions of pain expression.

Overall, the findings of [Table 6] are in strong agreement with existing literature, demonstrating that AI-based pain assessment systems have high sensitivity, specificity, and accuracy, making them valuable tools in palliative care. These results further support the potential of AI to improve pain detection, particularly in patients who are unable to communicate effectively.

## CONCLUSION

The present study was conducted to evaluate the role of Artificial Intelligence in pain assessment among palliative care patients and to compare its effectiveness with conventional pain assessment methods. The findings of the study demonstrate that AI-based pain assessment shows a **strong positive correlation with traditional tools** such as the Numeric Rating Scale, Visual Analogue Scale, and Behavioral Pain Scale, indicating good validity and reliability.

AI-based systems exhibited **high sensitivity, specificity, and overall diagnostic accuracy** in identifying moderate-to-severe pain, fulfilling the objective of assessing their effectiveness in clinical settings. Furthermore, AI demonstrated **consistent performance across both communicative and non-communicative patients**, with relatively better detection of pain in patients who were unable to self-report, thereby addressing a major limitation of conventional methods.

The comparative analysis confirms that AI-based assessment aligns closely with standard pain evaluation techniques while offering the additional advantage of **objectivity, reproducibility, and reduced observer bias**. Thus, all study objectives were successfully achieved, including assessment using conventional methods, evaluation through AI-based tools, comparison between the two approaches, and analysis of performance in non-communicative patients.

In conclusion, Artificial Intelligence can serve as a **reliable and effective adjunct tool in pain**

**assessment for palliative care patients**, particularly in complex clinical scenarios where subjective assessment is challenging. Its integration into routine clinical practice has the potential to enhance accuracy, improve patient care, and support better pain management strategies.

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