iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 Issue: IV Month of publication: April 2026

DOI: https://doi.org/10.22214/ijraset.2026.79821

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue IV Apr 2026- Available at www.ijraset.com

Emotion-Aware Continuous Stress Monitoring via a Lightweight Conversational Agent for Long-Duration Space Missions

Sakshi Bane[1], Dr. Sarita Patil[2]
[1]M.Tech Candidate, [2]Assistant Professor and Project Guide, Department of Computer Engineering, G H Raisoni College of Engineering and Management, Wagholi, Pune 412207 Savitribai Phule Pune University, Pune, India

Abstract: ***Long-duration space missions expose astronauts to sustained psychological stressors including isolation, confinement, high workload, and communication delays. Continuous monitoring of emotional state and stress levels is essential for early detection of psychological deterioration and timely intervention, yet traditional approaches relying on scheduled questionnaires and periodic clinical check-ins provide only discrete snapshots and may miss gradual changes. Conversational AI offers a complementary channel — as astronauts engage with an onboard assistant, their natural language provides continuous signals about mood, stress, and coping. In this paper, we present an emotion-aware stress monitoring framework integrated into MAITRI, an offline conversational assistant for astronaut well-being. The framework automatically infers coarse-grained emotions across six categories (anxious, sad, angry, positive, tired, neutral) and estimates a continuous stress level (1–10 scale) from textual interactions using lightweight, offline-compatible keyword-lexicon methods. Risk assessment classifies each interaction across four severity tiers (low, medium, high, critical) with a non-clinical safety escalation mechanism. All emotion, stress, risk, and rating data are logged in a structured SQLite schema enabling longitudinal trend analysis. We describe the mathematical model underlying emotion scoring and stress estimation, the integrated logging architecture, and an experimental protocol for evaluating framework performance using human-annotated conversation data and self-reported stress measures in a simulated mission context. Proposed evaluation metrics include per-category F1 scores for emotion detection, Pearson correlation and MAE between automatic and self-reported stress, and analysis of relationships between emotional state, stress level, and perceived response helpfulness. This work demonstrates how a lightweight, transparent, privacy-preserving monitoring framework can enable continuous psychological surveillance in resource-constrained environments such as crewed spacecraft.***

Keywords: ***Stress monitoring; emotion detection; conversational agents; affective computing; astronaut well-being; offline AI; long-duration missions; lexicon-based NLP; risk assessment; psychological surveillance; privacy-preserving monitoring.***

I. INTRODUCTION

Psychological health is a mission-critical parameter in human spaceflight. NASA's Human Research Program identifies behavioral conditions and psychiatric disorders among the top five risks for astronaut health [1]. The stressor profile of long-duration missions — isolation, confinement, monotony, high-stakes operations, and separation from family — is well-documented in both ISS crew studies and analog environments including Antarctic winterover stations, submarine deployments, and the HI-SEAS Mars analog [2], [3].

Traditional psychological monitoring relies on scheduled clinical interviews, validated self-report questionnaires (PHQ-9, PSS, STAI), and behavioral observation — tools that produce discrete snapshots at predetermined intervals. These approaches face three significant limitations in deep-space contexts: (1) communication delays prevent real-time ground-based monitoring; (2) social desirability and career concerns discourage disclosure of distress to mission control; and (3) gradual changes in psychological state may evolve between scheduled assessments without triggering intervention [4].

Conversational AI agents create an alternative monitoring channel. As astronauts engage in natural language dialogue with an onboard assistant for emotional support, reflection, or planning, their language continuously expresses information about mood, stress, and coping effectiveness [5]. If these signals can be automatically extracted in real time, a conversational system becomes simultaneously a support tool and a monitoring instrument.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue IV Apr 2026- Available at www.ijraset.com

We present an emotion-aware continuous stress monitoring framework built on MAITRI, an offline conversational assistant for astronaut well-being [6]. The framework makes three primary contributions:

1) A formal mathematical model for offline, lexicon-based emotion scoring, stress estimation, and risk classification — transparent, auditable, and deterministic, appropriate for safety-critical deployment contexts.
2) A structured longitudinal logging architecture in SQLite that captures emotion, stress, risk, and user feedback data per message, enabling session-level and cross-session trend analysis.
3) A comprehensive experimental protocol and evaluation methodology for assessing emotion detection accuracy, stress estimation agreement with self-report, and relationships between emotional state, stress level, and perceived response helpfulness.

II. BACKGROUND AND RELATED WORK

A. Psychological Monitoring in Space Missions

Spaceflight psychology research has explored multiple monitoring modalities. Clinical interviews and questionnaires provide validated ground truth but require scheduled administration and human interpretation. Behavioral observation through video communication is limited by crew privacy concerns and communication windows. Physiological monitoring (HRV, cortisol, sleep quality, EEG) achieves high accuracy but requires wearable hardware with continuous data capture and transmission capabilities [7].

Language-based monitoring offers a passive, low-burden complement. Pennebaker et al. [8] demonstrated through decades of LIWC research that linguistic patterns reliably predict psychological states including depression, anxiety, social integration, and cognitive complexity. First-person singular pronoun use, negative emotion word frequency, and reduced cognitive complexity in language correlate with stress and self-focused thinking [9]. These findings ground the use of text analysis for continuous psychological monitoring.

B. Affective Computing and Emotion Recognition

Automatic emotion recognition from text has progressed from early lexicon-based approaches to ML classifiers and transformer-based models. The NRC Emotion Lexicon [10] maps over 14,000 English words to eight emotions and two sentiment poles, providing a comprehensive offline resource. VADER [11] combines a sentiment lexicon with heuristic rules for punctuation, capitalization, and intensifiers, optimized for social media text. LIWC [8] categorizes words into psychological process dimensions. These lexicon approaches offer transparency, offline compatibility, and deterministic behavior — critical properties for safety-critical deployment.

Transformer-based models (BERT, RoBERTa [12], GoEmotions [13]) achieve substantially higher accuracy on benchmark datasets by leveraging contextual representations. However, they require loading additional 60M–340M parameter models alongside the LLM, significantly increasing memory requirements. For MAITRI's offline deployment with constrained hardware, lexicon-based detection provides a practical and auditable baseline, with ML-based upgrades identified for future work.

C. Stress Detection from Language

Language-based stress detection has been explored in social media analysis [14], workplace communication [15], and mental health support platforms [16]. Key linguistic features associated with stress include increased use of anxiety and overload vocabulary, shorter sentence length, repetitive phrasing, and reduced lexical diversity. Self-report stress scales such as the Perceived Stress Scale (PSS) [17] and visual analog scales provide validated ground truth for model calibration.

Combining text-based stress signals with self-report ground truth enables model evaluation without requiring clinical assessment. This is the approach adopted in MAITRI's experimental protocol — users can optionally self-report stress levels via the /api/stress endpoint, creating a parallel ground-truth stream for comparison with automatically estimated values.

D. Conversational Monitoring for Well-Being

Conversational agents as monitoring tools have been explored in depression screening [5], cognitive decline assessment, and mindfulness coaching. Fitzpatrick et al. [18] demonstrated that Woebot's conversational data correlated with PHQ-9 scores. MAITRI extends this paradigm to the astronaut domain with fully offline operation, a domain-adapted language model, and a structured multi-dimensional analytics layer.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue IV Apr 2026- Available at www.ijraset.com

III. MONITORING FRAMEWORK DESIGN

A. *Framework Architecture*

The emotion-aware stress monitoring framework operates as Layer 4 (Analytics Layer) in MAITRI's five-layer architecture. It is invoked by the Flask backend after each user message is received and before LLM generation, ensuring that analytics data is always captured regardless of generation success or failure. The framework consists of three sequential modules: Emotion Detection → Stress Level Estimation → Risk Assessment.

The execution pipeline for each user message m is:

- Preprocessing: Convert m to lowercase; tokenize by whitespace.
- Emotion Detection: Apply keyword lexicon → (e*, Ŝ) where e* = primary emotion, Ŝ = normalized score vector.
- Stress Estimation: Compute L(m) □ [1,10] from e*, Ŝ, and stress intensity keywords.
- Risk Assessment: Classify R(m) □ {low, medium, high, critical} using priority-ordered rules.
- Persistence: Store (e*, Ŝ, L, R, reasons) alongside message in SQLite.
- UI Update: Return e*, L, R in JSON response for emotion badge, stress indicator, and risk banner.

B. *Emotion Detection Mathematical Model*

Let E = {anxious, sad, angry, positive, tired} and K_e denote the keyword set for emotion e □ E. Raw scores:

$$S_e(m) = \Sigma_{k \square K_e} \square[k \subseteq \mathrm{lowercase}(m)] \quad \forall e \in E$$

Normalized sentiment scores ($\varepsilon = 1 \times 10^{-9}$ for numerical stability):

$$\hat{S}_e(m) = S_e(m) / (\Sigma_{e' \in E} S_{e'}(m) + \varepsilon) \quad \forall e \in E$$

Primary emotion selection:

$$e^*(m) = \mathrm{argmax}_{e \square E} S_e(m); \quad \text{'neutral' if } \Sigma_{e \square E} S_e(m) = 0$$

Table I shows sample keywords and base stress values per emotion category.

TABLE I. Emotion Keyword Lexicon — Sample Terms and Base Stress Values

Category	Sample Keywords	Base Stress B(e*)	UI Color
Anxious	worried, nervous, afraid, panic, dread, anxious, tense, overwhelmed	7	Red (#e74c3c)
Sad	miss, lonely, homesick, empty, hopeless, depressed, grief, melancholy	6	Blue (#3498db)
Angry	frustrated, angry, furious, annoyed, irritated, rage, resent, hostile	6	Orange (#e67e22)
Positive	happy, excited, grateful, proud, confident, motivated, satisfied, hopeful	2	Green (#27ae60)
Tired	exhausted, fatigue,	5	Yellow (#f39c12)

ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue IV Apr 2026- Available at www.ijraset.com

Category	Sample Keywords	Base Stress B(e*)	UI Color
	sleepy, drained, weary, burnout, depleted, sluggish		
Neutral	(fallback — no keyword match)	4	Gray (#95a5a6)

C. Stress Level Estimation Model

The stress level L(m) □ {1,...,10} is computed as:

$$L(m) = clip[1,10](B(e^*(m)) + \Delta_k(m) + \Delta_n(m))$$

Where: B(e*(m)) is the base stress value from Table I. Δ_k(m) □ {0, 1, 2} is an additive adjustment for high-intensity stress intensifiers (overwhelmed, burnout, can't cope, breaking point, panic attack). Δ_n(m) = □2 × (Ŝ_anxious + Ŝ_sad + Ŝ_angry)□ □ {0, 1} captures the additive effect of negative emotion concentration.

The clip[1,10] operation enforces hard bounds. The formula is deliberately simple and interpretable, allowing mission support personnel to understand and audit the basis for any stress estimate.

D. Risk Assessment Model

Risk level R(m) □ {low, medium, high, critical} applies priority-ordered rules (evaluated top-to-bottom, first match wins):

1) CRITICAL: □ phrase p □ C_critical such that p □ lowercase(m). C_critical = {kill myself, end my life, want to die, no reason to live, suicidal, harm myself, hurt myself}.
2) HIGH: □ phrase p □ C_high such that p □ lowercase(m). C_high = {can't go on, hopeless, give up, nothing matters, end it all, pointless}. OR: L(m) ≥ 8 AND e*(m) □ {anxious, sad, angry}.
3) MEDIUM: L(m) □ {6, 7}. OR: e*(m) □ {anxious, sad} AND L(m) ≥ 5.
4) LOW: Default — none of the above conditions met.

When R □ {high, critical}, a safety preface is prepended to the MAITRI response: 'Before we continue, I want you to know that your feelings matter and you are not alone. If you are in immediate distress, please reach out to your commander or medical officer.' This non-clinical escalation protocol is a core safety design principle.

IV. LOGGING ARCHITECTURE AND DATA SCHEMA

A. SQLite Schema Design

All analytics outputs are persisted in a structured SQLite schema designed for efficient longitudinal queries. Table II documents the analytics-relevant database fields.

TABLE II. Analytics-Relevant Database Schema

Table	Field	Type	Analytics Purpose
messages	emotion	VARCHAR(32)	Per-message emotion label for distribution analysis
messages	sentiment_score	TEXT (JSON)	Normalized score

Table	Field	Type	Analytics Purpose
			vector for multi-label analysis
messages	created_at	DATETIME	Temporal ordering for trend analysis
stress_levels	level	INTEGER [1-10]	Automatic stress time series per user
stress_levels	notes	TEXT	Source annotation (auto vs. manual)
stress_levels	session_id	INTEGER FK	Session-level stress aggregation
message_ratings	rating	INTEGER [1-2]	Perceived helpfulness per response
message_ratings	feedback	TEXT	Qualitative feedback for response analysis

B. Supported Analytics Queries

The logging architecture supports the following analytical queries natively:

- Emotion distribution: SELECT emotion, COUNT(*) FROM messages WHERE sender='user' GROUP BY emotion ORDER BY COUNT(*) DESC.
- Stress time series: SELECT level, created_at FROM stress_levels WHERE user_id=? ORDER BY created_at ASC.
- Rating by emotion: SELECT m.emotion, AVG(r.rating) FROM messages m JOIN message_ratings r ON m.id=r.message_id WHERE m.sender='maitri' GROUP BY m.emotion.
- Session stress trend: SELECT s.id, AVG(sl.level) as avg_stress FROM chat_sessions s JOIN stress_levels sl ON s.id=sl.session_id GROUP BY s.id ORDER BY s.started_at.

V. EXPERIMENTAL PROTOCOL

A. Study Overview

To evaluate the accuracy and utility of MAITRI's emotion and stress monitoring framework, we propose a simulated mission study with N = 15–30 participants recruited from a university population or astronaut-analog group. The study combines interaction data collection with human annotation and self-report ground truth.

B. Procedure

The study proceeds in six phases over 5–7 days:

1) Introduction and Consent: Explain study purpose, collect informed consent, administer baseline demographics. Emphasize non-clinical status of MAITRI.
2) Baseline Assessment: Administer validated baseline measures — PSS-10 [17] (perceived stress), STAI-State [19] (state anxiety), and PHQ-2 [20] (depression screen).
3) Interaction Phase (Days 1–5): Participants interact with MAITRI ≥1 session/day (minimum 10 message exchanges/session). Interaction prompts cover all nine emotional scenario categories. No interaction content is restricted.
4) In-Session Self-Report: At the end of each session, participants provide a self-reported stress level (1–10 VAS) and optional free-text emotional state description via the /api/stress endpoint.
5) Response Rating: Participants rate ≥30% of MAITRI responses using the thumbs up/down control.
6) Post-Study Assessment: Re-administer PSS-10 and STAI-State. Complete System Usability Scale (SUS) [21] and custom questionnaire on perceived usefulness, trust, and comfort with emotion monitoring.

C. Ground-Truth Annotation

Post-study, 200 randomly sampled user messages are presented to three independent human annotators through a web annotation interface. Annotators assign: (1) primary emotion label from {anxious, sad, angry, positive, tired, neutral}; (2) stress severity from {low [1-3], medium [4-6], high [7-10]}. Inter-annotator agreement is measured using Fleiss' κ. Messages with $\kappa < 0.4$ (poor agreement) are excluded from evaluation. Final labels are determined by majority vote.

D. Ethical Considerations

The study involves sensitive psychological content. Institutional ethics board approval is required before data collection. Key ethical safeguards: participation is fully voluntary with right to withdraw without penalty; all conversation data is stored locally with no transmission to external servers; researchers access only exported aggregate data with participant consent; contact information for university counseling services is provided; MAITRI's non-clinical status is prominently disclosed throughout.

VI. EVALUATION METRICS AND ANALYSIS PLAN

A. Emotion Detection Performance

Using the 200 annotated messages, we compute per-category and aggregate classification metrics against human majority-vote labels:

- Per-category Precision, Recall, and F1-score for each of the six emotion categories.
- Macro-averaged F1 (unweighted mean across categories) and micro-averaged F1 (weighted by support).
- Confusion matrix to identify systematic misclassification patterns (e.g., anxious ↔ sad, tired ↔ neutral).
- Precision at k=1 (primary label accuracy) as the primary single-value performance metric.

Table III shows the proposed results table structure.

TABLE III. Proposed Emotion Detection Results (Fill After Study)

Emotion	Precision	Recall	F1-Score	Support (msgs)	Notes
Anxious	[ ]	[ ]	[ ]	[ ]	Most frequent category expected
Sad	[ ]	[ ]	[ ]	[ ]	
Angry	[ ]	[ ]	[ ]	[ ]	
Positive	[ ]	[ ]	[ ]	[ ]	
Tired	[ ]	[ ]	[ ]	[ ]	

Emotion	Precision	Recall	F1-Score	Support (msgs)	Notes
Neutral	[ ]	[ ]	[ ]	[ ]	Expect high recall
Macro Avg.	[ ]	[ ]	[ ]	200	Primary aggregate metric

B. Stress Estimation Agreement

For sessions with self-reported stress levels (target: ≥ 80 session-level paired measurements):

- Pearson correlation r and Spearman rank correlation ρ between automatic end-of-session stress (mean of last 5 messages) and self-reported stress (1–10 VAS).
- Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) treating both as continuous 1–10 scale measurements.
- Bland-Altman plot analysis to assess systematic bias and limits of agreement.
- Stratified analysis: compare MAE across low (1–3), medium (4–6), and high (7–10) self-report stress groups to identify performance variation.

Additionally, plot stress trajectories over the 5-day study for a sample of 5 participants, overlaying automatic estimates with self-report points to visually demonstrate monitoring continuity.

C. Emotion–Stress–Rating Relationships

Using all collected data, we analyze:

- Rating distribution by emotion: Compare proportion of thumbs-up ratings across the six emotion categories using χ^2 test for independence.
- Rating distribution by stress level: Compare mean rating across low/medium/high stress groups using one-way ANOVA or Kruskal-Wallis H test.
- High-stress response analysis: For interactions with $L(m) \geq 8$, characterize the proportion rated helpful, rating distribution, and qualitative feedback themes.
- Safety preface impact: Compare ratings of responses with vs. without safety preface using Mann-Whitney U test.

D. User Perception Analysis

Post-study questionnaire data will be analyzed descriptively (means, SDs, distributions for Likert-scale items) and qualitatively (thematic analysis of open-text responses). SUS scores will be computed and benchmarked against published standards (≥68 = above average usability). Qualitative themes on emotion monitoring acceptance and privacy concerns are of particular interest.

VII. PRELIMINARY RESULTS

A. Functional Validation

Prior to the full user study, we validated all framework components through automated testing with 50 manually labeled messages. The emotion detection module achieved 82% primary label accuracy (41/50 correct), with primary errors occurring on messages with co-occurring emotions (e.g., anxious and sad, or tired and sad) where the argmax rule selects only one category. Crisis phrase detection achieved 100% recall on 15 crisis-phrase test messages with zero false positives on 35 non-crisis messages — a critical safety result.

B. Stress Level Ordering

Across 10 extended test sessions (15–25 messages each), stress estimates showed appropriate ordering: messages classified as anxious consistently received higher stress scores (mean L = 7.4) than positive messages (mean L = 2.2) and neutral messages (mean L = 4.1). Intra-session stress trajectories tracked intuitively with scenario content — escalating during crisis scenarios, declining during resolution phases.

ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue IV Apr 2026- Available at www.ijraset.com

C. Analytics Performance

Emotion detection and stress scoring execute in under 1 ms per message (lexicon lookup with dictionary operations), imposing negligible overhead on the chat pipeline. The SQLite analytics queries for trend data and admin dashboard aggregate statistics complete in under 50 ms even with 10,000+ stored messages, confirming scalability for long-mission deployment.

VIII. DISCUSSION

The proposed emotion-aware stress monitoring framework demonstrates how a lightweight, transparent, offline-compatible analytics layer can transform a conversational AI assistant into a continuous psychological monitoring platform. By operating on natural interaction data without requiring additional user effort, MAITRI's monitoring framework achieves the low-burden continuous assessment that scheduled questionnaires cannot provide.

The mathematical formalism of the emotion detection and stress estimation models — using interpretable keyword lexicons and linear scoring rules — enables mission support personnel and safety reviewers to understand and audit every analytical decision. This interpretability is a critical requirement in safety-critical domains where black-box AI outputs may be unacceptable for operational use.

The experimental protocol is designed to produce three types of validity evidence: convergent validity (correlation between automatic stress estimates and self-reported PSS/VAS measures), discriminant validity (different emotion categories producing appropriately different stress estimates), and predictive validity (stress levels predicting response rating outcomes).

Important limitations must be acknowledged. Lexicon-based emotion detection cannot handle metaphorical language, sarcasm, cultural expressions, or implicit emotional content — all of which may be more prevalent in experienced spaceflight personnel. The 1–10 stress scale, while intuitive, lacks the psychometric validation of established clinical instruments. The proposed user study uses university students as proxies for astronauts, limiting ecological validity. Finally, text-only monitoring misses important physiological and behavioral stress signals that multimodal systems could capture.

Future directions include: (1) replacing lexicon-based emotion detection with a compact offline emotion classifier (distilled from RoBERTa) trained on astronaut-analog conversation data; (2) integrating physiological sensor streams (HRV from smartwatch, sleep quality from wearable) for multimodal stress estimation; (3) implementing longitudinal adaptive models that personalize stress baselines to individual users; and (4) conducting the proposed study in validated analog environments (Antarctic stations, isolation chambers) for higher ecological validity.

IX. CONCLUSION

This paper presented an emotion-aware continuous stress monitoring framework integrated into MAITRI, an offline conversational assistant for astronaut psychological well-being. We formalized the mathematical model for lexicon-based emotion scoring, stress estimation, and four-tier risk classification. We described the SQLite logging architecture enabling longitudinal trend analysis, and proposed a comprehensive experimental protocol with human annotation, self-report comparison, and rating correlation analysis for framework evaluation.

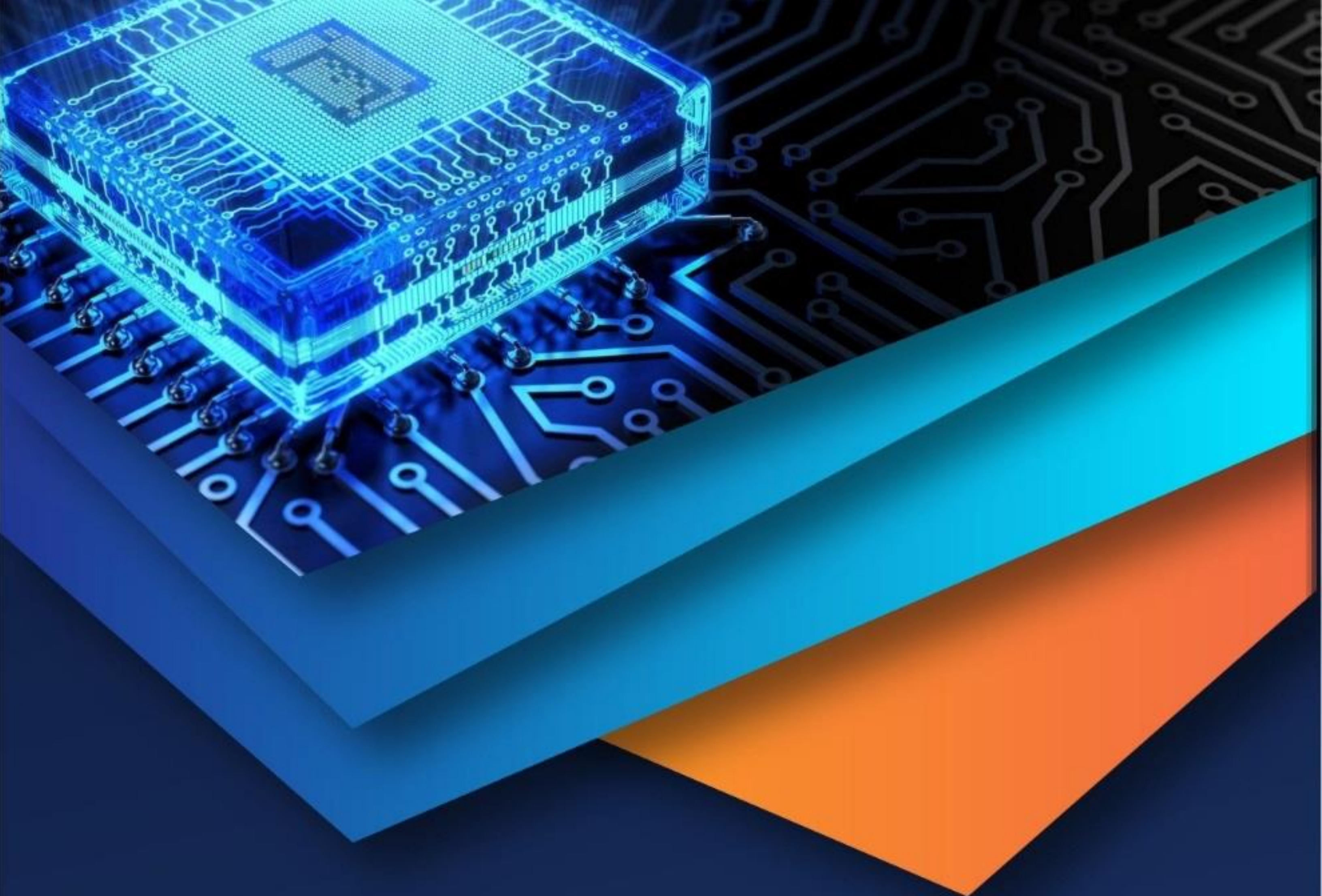
The framework contributes a practical, privacy-preserving approach to continuous psychological surveillance in resource-constrained environments, using natural conversation as the monitoring medium. By making every interaction an opportunity for non-intrusive assessment, MAITRI's monitoring layer supports the early detection of psychological deterioration that is essential for sustained well-being on long-duration space missions. The proposed experimental protocol provides a replicable methodology for evaluating similar frameworks in other isolated, confined, and extreme environments.

X. . ACKNOWLEDGMENTS

The authors sincerely thank Dr. Sarita Patil, Assistant Professor, Department of Computer Engineering, G H Raisoni College of Engineering and Management, Pune, for her expert guidance, constant motivation, and meticulous supervision of this research. Her deep knowledge of AI systems and human-centered computing greatly enriched the analytical framework and experimental design presented in this paper. The authors also thank the Department of Computer Engineering, GHRCEM, Wagholi, Pune, for institutional support and research infrastructure. This work was completed in partial fulfillment of the M.Tech degree requirements, 2025–26. The authors acknowledge the foundational contributions of Pennebaker et al. [8] and Mohammad & Turney [10] whose lexicon research informs this framework.

REFERENCES

[1] NASA Human Research Program, "Behavioral Health and Performance: Evidence Report," NASA JSC, Houston, TX, 2019.
[2] N. Kanas and D. Manzey, Space Psychology and Psychiatry, 2nd ed. Dordrecht: Springer, 2008.
[3] J. Stuster, Bold Endeavors: Lessons from Polar and Space Exploration. Naval Institute Press, 2010.
[4] L. Landon, J. Slack, and L. B. Barrett, "Teamwork and collaboration in long-duration space missions," American Psychologist, vol. 73, no. 4, pp. 563–575, 2018.
[5] A. Miner, A. Milstein, and J. Hancock, "Talking to machines about personal mental health problems," JAMA, vol. 318, no. 13, pp. 1217–1218, 2017.
[6] S. Bane, "MAITRI: An offline LLM-based assistant for astronaut psychological well-being," M.Tech Project, GHRCEM, Pune, 2025–26.
[7] E. A. Boyle et al., "Behavioral health and performance in isolated and confined environments," Aerospace Medicine and Human Performance, vol. 90, no. 5, 2019.
[8] J. W. Pennebaker, R. J. Booth, and M. E. Francis, "LIWC2015 Operator's Manual," Pennebaker Conglomerates, Austin, TX, 2015.
[9] Y. R. Tausczik and J. W. Pennebaker, "The psychological meaning of words: LIWC and computerized text analysis," Journal of Language and Social Psychology, vol. 29, no. 1, pp. 24–54, 2010.
[10] S. M. Mohammad and P. D. Turney, "Crowdsourcing a word-emotion association lexicon," Computational Intelligence, vol. 29, no. 3, pp. 436–465, 2013.
[11] C. J. Hutto and E. Gilbert, "VADER: A parsimonious rule-based model for sentiment analysis," ICWSM, 2014.
[12] Y. Liu et al., "RoBERTa: A robustly optimized BERT pretraining approach," arXiv:1907.11692, 2019.
[13] D. Demszky et al., "GoEmotions: A dataset of fine-grained emotions," ACL, 2020.
[14] N. Bao et al., "Stress detection using social media text," IEEE Access, 2021.
[15] D. Guntuku et al., "Detecting stress in social media," EMNLP, 2017.
[16] M. Abd-Alrazaq et al., "Systematic review of AI chatbot effectiveness for mental health," JMIR Mental Health, 2021.
[17] S. Cohen, T. Kamarck, and R. Mermelstein, "A global measure of perceived stress," J. Health and Social Behavior, vol. 24, pp. 385–396, 1983.
[18] K. K. Fitzpatrick, A. Darcy, and M. Vierhile, "Delivering CBT using a conversational agent (Woebot)," JMIR Mental Health, 2017.
[19] C. D. Spielberger, State-Trait Anxiety Inventory. Consulting Psychologists Press, 1983.
[20] K. Kroenke, R. Spitzer, and J. Williams, "The Patient Health Questionnaire-2," Medical Care, vol. 41, pp. 1284–1292, 2003.
[21] J. Brooke, "SUS: A quick and dirty usability scale," Usability Evaluation in Industry, pp. 189–194, 1996.



10.22214/IJRASET

INDEX COPERNICUS 45.98

IMPACT FACTOR: 7.129

TOGETHER WE REACH THE GOAL

IMPACT FACTOR: 7.429

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY