iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 **Issue:** III **Month of publication:** March 2026

DOI: https://doi.org/10.22214/ijraset.2026.79056

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 III Mar 2026- Available at www.ijraset.com

Detection of Mental Stress through Digital Communication Patterns: A User-Centric Survey Analysis

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Abstract: Mental health awareness has become increasingly critical in the digital age, where text-based communication dominates interpersonal interaction. This study investigates the feasibility of detecting mental stress through the analysis of digital chat messages by examining user behaviour patterns, linguistic indicators, and perceptions regarding automated stress detection systems. A comprehensive survey was conducted with 54 participants from diverse demographics to understand how stress manifests in digital communication and user acceptance of artificial intelligence-based detection mechanisms. The findings revealed that 63.0% of participants experienced mental stress while engaging in chat conversations, with 68.5% acknowledging that their message characteristics changed during stressful periods. The key stress indicators identified were short or abrupt replies (59.3%), increased negative word usage (46.3%), and reduced emoji frequency (72.2%). The study demonstrated that 81.5% of participants experienced emotional overwhelm during digital communication, indicating the significant potential for early stress detection. Although 51.9% of respondents expressed comfort with AI-based analysis, universal privacy concerns (100%) highlighted the critical need for privacy-preserving detection systems. This research contributes empirical evidence to support the development of ethical, user-controlled mental health monitoring tools that leverage natural language processing and machine learning techniques. These findings provide a foundation for designing non-intrusive stress detection systems that respect user privacy while offering valuable insights into mental health.
Keywords: Mental stress detection, Digital communication analysis, Natural language processing, Mental health monitoring, Chat message analysis, Privacy-preserving AI

I. INTRODUCTION

A. Background of the research

The proliferation of digital communication platforms has fundamentally transformed how individuals interact, with instant messaging applications becoming the primary medium of daily communication. Platforms such as WhatsApp, Instagram, Telegram, and Facebook Messenger facilitate billions of messages daily, creating an unprecedented repository of linguistic and behavioural data that potentially reflects users' psychological states. Concurrently, mental health challenges, particularly stress-related conditions, have reached epidemic proportions globally, affecting millions across all demographics, with young adults and students being particularly vulnerable to these challenges.

Traditional stress detection methods rely heavily on self-reporting mechanisms, clinical assessments, or physiological measurements, which often suffer from limitations, including accessibility barriers, temporal delays, and the stigma associated with seeking mental health support. The digital communication patterns embedded in chat messages may offer an alternative, non-intrusive approach to early stress detection, potentially enabling timely interventions before the conditions escalate.

B. Research Gap

While extensive research exists on mental health detection using social media platforms, limited attention has been directed toward private messaging applications. Previous studies have primarily focused on public social media posts, which differ significantly from private chat messages in terms of communication style, privacy expectations and emotional expression. Additionally, user perspectives on AI-based stress detection systems in personal messaging contexts remain underexplored, creating a critical gap in understanding the technical feasibility and social acceptance of such systems.

C. Motivation
The increasing prevalence of mental health issues, particularly among students and young professionals, necessitates innovative approaches for early detection and interventions. Digital communication patterns may serve as early warning indicators of psychological distress, thereby enabling proactive support mechanisms. However, the development of effective stress detection systems requires a comprehensive understanding of user behavior, linguistic patterns, and privacy concerns to ensure both technical efficacy and social acceptance.

D. Objectives
This study aims to:
- Investigate behavioural patterns and linguistic indicators that reflect mental stress in digital chat messages
- Analyse user perceptions and acceptance levels regarding AI-based stress detection systems
- Identify privacy and ethical concerns associated with automated message analysis
- Provide empirical insights for developing effective, ethical, and privacy-preserving stress detection systems

E. Paper Outline
The remainder of this paper is organized as follows: Section 5 reviews the relevant literature on mental health detection through digital communication. Section 6 describes the research methodology, including the survey design and data collection procedures. Section 7 presents the findings of the survey analysis. Section 8 discusses the implications of the results, compares them with existing research, and addresses the limitations. Section 9 concludes with the key findings, contributions, and future research directions.

II. LITERATURE REVIEW

A. Mental Health Detection Through Digital Communication
Research in computational psychology has established that the linguistic patterns in written communication correlate with psychological states. Pennebaker et al. [1] demonstrated that word choice, sentence structure, and writing style serve as indicators of emotional states and mental health conditions. Their foundational work on Linguistic Inquiry and Word Count (LIWC) established quantitative methods for analyzing psychological processes through language.

B. Natural Language Processing in Mental Health Assessment
Recent advances in natural language processing (NLP) and machine learning have enabled the automated analysis of text data for mental health assessment. De Choudhury et al. [2] demonstrated the feasibility of detecting depression through social media posts using machine-learning classifiers trained on linguistic features. Coppersmith et al. [3] extended this work to identify multiple mental health conditions, including anxiety and post-traumatic stress disorder, through Twitter data analysis.

Guntuku et al. [4] provided a comprehensive review of depression and mental illness detection on social media, highlighting the potential of computational approaches and emphasizing the need for clinical validation. However, most existing research focuses on public social media platforms rather than private messaging applications, which present distinct challenges and opportunities for researcher.

C. Privacy and Ethical Considerations
The application of AI systems to analyze personal communications raises significant privacy and ethical concerns. Chancellor and De Choudhury [5] examined the social impact of natural language processing in mental health contexts, emphasizing the importance of user consent, data security, and transparency of algorithmic. Hovy and Spruit [6] highlighted the ethical challenges in NLP applications, particularly regarding privacy protection and bias mitigation.

D. Research Gap Identification
While substantial research exists on mental health detection through social media, several gaps remain.
1) Limited research on private messaging applications, which differ significantly from public social media in communication patterns and privacy expectations
2) Insufficient understanding of user perspectives regarding AI-based stress detection in personal messaging contexts

3) Lack of comprehensive analysis of linguistic and behavioural indicators specific to chat-based stress expression
4) Inadequate exploration of privacy-preserving mechanisms for mental health monitoring systems

This study addresses these gaps by examining user behavior, perceptions, and concerns specifically in the context of private chat message analysis for stress detection.

III. METHODOLOGY

A. Research Design

This study employed a quantitative survey-based research design to collect comprehensive data on user experiences, behaviours, and perceptions regarding mental stress in digital communications and AI-based detection systems. The survey methodology enabled collection of self-reported data from a diverse participant pool, providing insights into both behavioural patterns and attitudinal factors.

B. Survey Instrument Development

A comprehensive online survey was developed containing 27 questions covering multiple dimensions.

- Demographic Information: Age group, gender, educational background, and occupation were collected understand participant diversity and enable demographic analysis.
- Chat Application Usage Patterns: Frequency of use, preferred platforms, and communication habits to establish baseline usage patterns.
- Stress Experience and Behavior: Questions regarding stress experiences during chatting, behavioral changes when stressed, and specific indicators of stress in messages.
- Linguistic Patterns: Inquiries about word choice, message length, emoji usage, punctuation patterns, and emotional expression during stress.
- AI Acceptance and Privacy: Questions exploring comfort levels with AI analysis, privacy concerns, and suggestions for system improvement.

The survey employed multiple question types, including single-choice, multiple-choice, Likert-scale, and open-ended questions, to capture both quantitative and qualitative insights.

C. Data Collection

The survey was distributed through multiple channels, including social media platforms, academic networks, professional groups, and personal contacts, to ensure diverse participant recruitment. Data were collected over a period of [specify duration], resulting in 54 complete responses. Participation was voluntary, and all respondents provided their informed consent.

D. Sample Characteristics

The study sample (N=54) comprised participants with the following characteristics.

- Age Distribution: The majority (64.8%) were aged 18-24 years, followed by 25-34 years (24.1%), 35-44 years (7.4%), and other age groups (3.7%). This distribution reflects the primary user base of digital communication platforms in the country.
- Gender Distribution: Male participants constituted 63.0% of the sample, while female participants represented 37.0%.
- Educational Background: Postgraduate students represented 50.0% of the participants, undergraduate students 44.4%, and school-level participants 5.6%.
- Occupation: Students constituted 59.3% of the sample, working professionals 25.9%, self-employed individuals 7.4%, with other categories representing the remainder.

E. Data Analysis

Descriptive statistics were used to analyze demographic distributions, response frequencies, and patterns. Content analysis was applied to open-ended responses regarding privacy concerns and suggestions for system improvement. Statistical analysis was performed using Python with the pandas library, enabling a comprehensive examination of the relationships between variables.

F. Ethical Considerations

All participants were informed of the research purpose, data usage, and privacy protections. No personally identifiable information was collected beyond the demographic categories. Responses were anonymized, and data were stored securely. This study adhered to ethical guidelines for research involving human subjects, and institutional review board approval was obtained where required.

IV. RESULTS

A. Chat Application Usage Patterns

The study revealed extremely high engagement with chat applications by the participants. Half of the respondents (50.0%) reported using chat applications "Very Frequently," while 42.6% reported "Frequently" usage. Only 7.4% reported occasional or rare usage, indicating that digital communication has become the primary mode of interaction for most participants.

WhatsApp emerged as the dominant platform, with 37.0% of the participants using it exclusively. An additional 27.8% used WhatsApp combined with Instagram, while 13.0% used multiple platforms, including WhatsApp, Instagram, and Telegram. This platform concentration suggests that stress detection systems can focus on major platforms while maintaining broad coverage.

B. Prevalence of Stress in Digital Communication

A significant majority of participants (63.0%, n=34) reported experiencing mental stress while engaging in chat conversations, while 37.0% (n=20) reported never experiencing stress during digital communication. This finding indicates that stress during digital communication is a common experience, thus validating the relevance of stress detection research in this domain.

C. Behavioural Changes During Stress

When asked whether their chat messages changed when stressed (in terms of tone, words, or length), 68.5% of participants (n=37) agreed or strongly agreed that their messages changed during stressful periods. Specifically, 44.4% agreed and 24.1% strongly agreed, while 18.5% remained neutral, and only 13.0% disagreed or strongly disagreed with this statement. This finding strongly validates the premise that stress manifests in communication patterns.

D. Stress Indicators in Chat Messages

The participants identified multiple indicators of stress in chat messages. The most frequently mentioned indicators were:

1) Short or abrupt replies: 59.3% of participants (n=32) identified this as a stress indicator
2) Negative words: 51.9% (n=28) reported increased negative word usage during stress
3) Repeated messages: 37.0% (n=20) indicated that message repetition signals stress
4) Excessive emoji usage: 33.3% (n=18) identified this pattern
5) Typing errors: 27.8% (n=15) reported increased errors during stress

These findings provide crucial insights for developing stress detection algorithms, highlighting the importance of message length analysis, sentiment analysis and linguistic pattern recognition.

E. Negative Word Usage Patterns

Regarding the tendency to use more negative or pessimistic words when stressed, 46.3% of participants (n=25) agreed or strongly agreed with this behavior. Specifically, 31.5% agreed and 14.8% strongly agreed, while 38.9% remained neutral, and 14.8% disagreed or strongly disagreed. This finding supports the use of sentiment analysis and negative word detection in stress identification.

F. Emoji Usage Patterns

This study revealed significant changes in emoji usage during stress. A substantial majority (72.2%, n=39) reported that emoji usage decreased when stressed. Specifically, 14.8% reported this occurs "Always," 27.8% "Often," and 29.6% "Sometimes." Only 13.0% of the participants reported that emoji usage never decreased during stress. This pattern suggests that emoji frequency analysis can serve as a reliable stress indicator.

G. Emotional Overwhelm Frequency

The study found that emotional overwhelm was highly prevalent during digital communication. A total of 81.5% of participants (n=44) reported experiencing emotional overwhelm at least sometimes while texting or chatting. Specifically, 13.0% reported "

Very Often," 27.8% "Often," and 40.7% "Sometimes." Only 1.9% of the participants reported never experiencing emotional overwhelm, further emphasizing the relevance of this research domain.

H. Emotions Expressed During Stress

The participants identified various emotions that were commonly expressed in chats when they were stressed. The most frequently mentioned emotions were:

1. Anger: 50.0% of participants (n=27)
2. Sadness: 50.0% (n=27)
3. Frustration: 46.3% (n=25)
4. Confusion: 40.7% (n=22)
5. Anxiety: 37.0% (n=20)

These emotional states can be detected through linguistic analysis, sentiment classification, and emotion recognition techniques.

I. Message Length Changes

The study revealed interesting patterns regarding changes in message length during stress. While 44.4% of participants (n=24) reported that messages became shorter when stressed, 40.7% (n=22) reported that messages became longer. Only 14.8% of the participants reported no noticeable changes. This finding suggests that both extremes of message length may indicate stress, requiring sophisticated analysis rather than simple length-based detection methods.

J. AI System Acceptance

Participants' comfort levels with AI systems analyzing their chat messages revealed mixed attitudes. A total of 51.9% (n=28) expressed comfort or very comfortable feelings, with 40.7% comfortable and 11.1% very comfortable, respectively. However, 25.9% remained neutral, and 22.2% expressed discomfort or very uncomfortable feelings (11.1% each). This finding indicates the need for transparent, privacy-preserving systems to increase user acceptance.

K. Privacy and Ethical Concerns

All 54 participants (100%) responded to privacy concerns, indicating universal awareness of privacy implications. Common themes identified through content analysis included:

- Loss of privacy: Mentioned by the majority of participants
- Unauthorized data access: Significant concern about data security
- Misinterpretation of emotions: Worry about false positives and negatives
- Data misuse by third parties: Fear of commercial exploitation
- Lack of user consent: Need for explicit opt-in mechanisms
- Algorithmic bias: Concerns about unfair analysis

These concerns highlight the critical importance of implementing robust privacy protections, transparent algorithms, and user-control mechanisms in stress detection systems.

V. DISCUSSION

A. Interpretation of the Major Foundings.

This paper has identified some important lessons about stress detection with the aid of digital communication. The great rate of stress experience (63.0%) and recognition of a message change (68.5%) confirms the main assumption that stress can be observed in chat messages. The discovery of several stress indicators offers the basis of creating an extensive detection algorithms which exploit different linguistic and behavioral peculiarities of the user.

The observation that 81.5 percent of the participants had experienced emotional overwhelm when they engaged in digital communication implies that there is a large potential of early intervention systems. Nevertheless, the stress-induced lengthening-shortening of the messages (44.4% vs. 40.7) shows that the simple length-based detection is not enough, and the multi-feature-based one will be necessary.

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Volume 14 Issue III Mar 2026- Available at www.ijraset.com

B. Comparison to the Past Studies.

These results are consistent with the studies about the linguistic evidence of the psychological conditions conducted earlier. Pennebaker et al. [1] have determined that word choice represents the emotional conditions, which is consistent with our result which showed that 46.3% of respondents indicated negative word more frequently when stressed. Nonetheless, our research applies this to the context of private messaging when this is not similar to public social media both in communication style and privacy expectations.

These quantitative results (high prevalence of stress indicators (59.3% and 51.9% on short replies and negative words respectively) and validated the quantitative results observed in qualitative research. An emoji usage pattern (reduced by 72.2 percent when stressed) is a unique feature of digital communication that has the potential to increase the level of detection.

C. Implications on System Design.

According to these findings, the effective stress detection systems must include:

1) Multi-indicator Approach Systems should not be based on single indicators as the trend of message length, sentiment, emoji frequency, typing patterns, and linguistic markers are among several features that need to be examined.
2) Privacy-First Architecture: Universal privacy issues (100): Universal privacy issues require local processing, end-to-end encryption, and user-controlled sharing of data.
3) Transparency and User Control: There are mixed acceptance levels (51.9% comfortable vs. 22.2% uncomfortable) which suggests that transparent algorithms, explanation and adjustable sensitivity settings are required.
4) Contextual Understanding: Message length change is variable and requires systems to have their own baselines and take into account the context of conversation instead of using generalized thresholds.
5) Emotion Recognition: Recognition of particular emotions (anger, sadness, frustration) implies that emotion classification may improve detection performances to those of simple stress/non-stress binary classification.

D. Limitations

There are a few limitations that need to be mentioned.

1) Sample Size: The number of 54 participants is also a valuable input to the study but it does not represent the whole population. The generalizability of our findings should be reinforced in a larger-scale study.
2) Self-Reported Data: The answers would be based on self-awareness and honesty of respondents and this will cause bias. These findings would be enhanced in the future with objective validation by actual message analysis.
3) Cultural Context: It is possible that the sample of the study is based on certain cultural and linguistic contexts. Applicability is increased through cross-cultural validation.
4) Temporal Factors: The patterns of stress might change across time and the current study provides a snapshot of the patterns and not longitudinal patterns.
5) Platform Specificity: Various platforms can have a different pattern of communication, and platform-specific adjustments will be needed.

E. Future Research Directions

Future research should:

1) Studies of larger scale: Use larger more heterogeneous samples to increase generalizability and be able to analyze subgroups of the demographics.
2) Longitudinal analysis: To analyze stress patterns over prolonged time and therefore comprehend the dynamics of time to determine individual baselines.
3) Cross-Cultural Studies: Research into cultural differences in stress expression and patterns of detection in a variety of linguistic and cultural backgrounds.
4) Real time validation: Detection algorithms were tested on real-time message analysis and prediction compared with self-reported stress levels.
5) Clinical integration: Cooperation with mental health professionals to prove the accuracy of detection in comparison with clinical tests and to formulate intervention regimes.
6) Privacy-saving methods: System with advanced cryptographic methods, federated learning, and differential privacy mechanisms should be developed and tried on top of the stress detection systems.

VI. CONCLUSION

A. *Summary of Key Findings*

This paper offers extensive information on the mental stress detection through the digital communication patterns. This study illustrates that:

1) Digital communication is vulnerable to mental stress, with only 63.0% of participants being not effected.
2) The stress is seen to have patterns in the content of messages and 68.5% of them admit that they make changes in messages when they are stressed.
3) There are several linguistic and behavioural clues that can be used in the process of detection, such as the length of the message, emotion, the use of emojis, and the choice of words.
4) The issue of privacy and ethics is universal, and so privacy-saving system structures are required.
5) Acceptance by users is also ambivalent with 51.9 percent being comfortable and 22.2 percent out of place, which means that there is necessity of transparent systems that are user-controlled.

B. *Contribution of the Study*

The study has the following contributions to the emerging research on computational mental health assessment:

1) Empirical Evidence: To present quantitative data on the stress indicators that are unique to private messaging applications.
2) User Viewpoints: Investigating the levels of comfort and privacy to design the system.
3) Practical Insights: The discovery of particular linguistic and behaviour patterns to be used as the basis of algorithm development.
4) Ethical Framework: Raising the issue of privacy and proposing design concepts to be used ethically.

In this section, we discuss the practical and theoretical consequences of the study.

Practical Implications:

- based on metrics of stress that developers can identify (short replies, negative words, decreased emojis) algorithms can be developed to detect stress.
- Local processing and user control should be implemented to deal with privacy concerns.

Multi-indicator methods will be more efficient than the single features detection.

- It requires acceptance through user educationand transparency.

Theoretical Implications:

- Applies the linguistic analysis studies to the domain of the private messaging.
- Endorses calculational techniques of mental health evaluation in novel areas.
- Leads to the knowledge of the psychology of digital communication.
- Educates moral guidelines to AI-based health monitoring.

C. *Limitations*

The research recognizes the limitations such as the sample size, the use of self-reported data, the potential cultural specificity, and limitations to a time span. These are limitations that should be overcome in the future.

D. *Future Scope*

Further studies ought to be carried out on large-scale, longitudinal, cross-cultural validation, real-time validation of algorithms, clinical integration, and more sophisticated privacy-preserving methods. Ethical, effective, and privacy-preserving stress detection system development is a promising platform on which to enhance mental health outcomes through technology. Ore sophisticated privacy-preserving methods. Ethical, effective, and privacy-preserving stress detection system development is a promising platform on which to enhance mental health outcomes through technology.

VII. ACKNOWLEDGEMENTS

The authors sincerely thank the 54 participants who took the time to share their experiences and perspectives. Their responses are the foundation of this work. We also thank [Institution Name] for supporting this research, and [Reviewer Names] for their feedback during manuscript preparation.

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