SvedbergOpen
DISSEMINATION OF KNOWLEDGE

International Journal of Artificial Intelligence and Machine Learning

Publisher's Home Page: https://www.svedbergopen.com/

Research Paper Open Access

Natural Language Processing-Driven Sentiment And Mental Health Analysis Using Social Media Healthcare Data

Dr. Mira Das[1], Dr.Indumathi S M[2], Shree Jayaram K[3], Namrata Somnath Bajare[4], Tanveer Ahmad Wani[5], Parul Maurya[6], Mr. Gopalakrishnan N[7], Priyadharshini K[8]

[1]Professor , Department of Chemistry, Institute of Technical Education and Research, Siksha 'O' Anusandhan (Deemed to be University), Bhubaneswar, Odisha, India, Email :miradas@soa.ac.in,Orcid Id - 0000-0002-8476-2146
[2]Assistant Professor, Department of Biotechnology, Sathyabama Institute of Science and Technology, Chennai, Tamilnadu, India, Email: indumathi.biotech@sathyabama.ac.in, Orcid Id - 0000-0003-0854-0733
[3]Department of Research, Innovation & Incubation Centre, Meenakshi Academy of Higher Education and Research, Chennai, Tamil Nadu, India, Email: shreejayaram@maher.ac.in
[4]Department of Computer Engineering, Vishwakarma Institute of Technology, Pune, Maharashtra, 411037, India. Email: namrata.bajare@vit.edu
[5]Professor, School of Sciences,Noida International University,Uttar Pradesh 203201,India. Email: tanveer.ahmad@niu.edu.in
[6]Assistant Professor, Department of Environmental Science, Department of Environmental Science, Parul Institute of Applied Sciences, Parul University, Vadodara, Gujarat, India, Email: PARUL.MAURYA32967@paruluniversity.ac.in , Orcid Id- 0000-0002-8217-1422
[7]Assistant Professor, Department of Civil Engineering, Presidency University, Bengaluru, Karnataka, India, Email: gopalakrishnan@presidencyuniversity.in, Oercid Id - 0000-0003-3924-6705
[8]Department of Management Studies, Assistant Professor,Meenakshi College of Arts and Science, Meenakshi Academy of Higher Education and Research, Chennai, Tamil Nadu, India, Email: kpriyamba@maher.ac.in

Abstract

The growing social isolation, emotional instability, digital addiction and psychological pressure of the current patterns of online interaction have led to a greater prevalence of mental health disorders. The constantly growing human emotional expression in social media posts, comments, behavioral interactions and textual communications forms a scale of digital behavioral data that can be analyzed intelligently through the use of artificial intelligence. In this paper, we outline a Natural Language Processing-based Sentiment and Mental Health Analysis Framework of Social Media Healthcare Data that provides a temporal emotional modeling, transformer-enhanced semantic learning, emotional volatility prediction, explainable linguistic interpretation, and psychological trajectory prediction to adapt to mental health. The suggested framework presents a behavior sentiment drift model that can follow the changes in emotions and long-term psychological development based on the contextual language embeddings produced as a result of communicating on social media. In contrast to the traditional sentiment classification systems, where research only considers the positive and negative polarity detection, the proposed approach examines emotional persistence, depressive language development, anxiety changes, and behavioral instability patterns of the temporal communication patterns. The framework also includes explainable artificial intelligence strategies of recognising psychologically swaying linguistic phrases and understandable emotional logic. Experimental analysis shows the great improvement in the prediction of depression, estimation of emotional volatility, contextual sentiment comprehension and the analysis of the real time psychological trajectory relative to the traditional machine learning and recurrent neural network models. The suggested framework thus offers scalable and smart healthcare analytics, which can be used to actively assess mental health and identify early signs of psychological risks through the use of social media healthcare communication.

Keywords: Natural language processing; Mental health analytics; Sentiment drift modeling; Emotional volatility; Psychological trajectory prediction; Explainable artificial intelligence; Social media healthcare.

1. Introduction

The fast development of digital means of communication has essentially altered how people convey emotions, opinions and psychological experiences in the contemporary society. Interactions via social media are becoming more and more emotionally unstable, depressive, anxiety-induced and exhibiting signs of stress and behavioral variability that are linked to mental illnesses. As a result, the online healthcare communication has gained significance in terms of its importance in comprehending the psychological well-being and patterns of emotional progress in the population of large-scale groups. Traditional methods of mental healthcare assessment are mainly based on delayed clinical assessment, interviews with the therapist and self-reported emotional measures that in most cases do not represent the continuous emotional changes and the change in behavior. Conversely, communication via the social media offers dynamic time-based evidence of emotional development and progression of psychological pathways by patterns of language use, frequency of communication, semantic polarity and contextual emotional variability. Technologies of natural language processing have thus become an attractive means of adaptive mental health tracking and analytics of psychological healthcare on a large scale (Devlin et al., 2019; Vaswani et al., 2017). The newest developments in contextual transformer architecture, semantic embedding model, and intelligent communication systems have greatly enhanced the ability to represent emotions and comprehend the context in healthcare applications (Pennington et al., 2014; Mzeh et al., 2025). Additionally, omnipresent smart health care setups and signal-boosting solutions have facilitated scalable and distributed mental health care analytics to digital communication ecosystems (Salwadkar, 2025; Anderson, 2025). Nevertheless, most of the current sentiment analysis systems only address the issue of stationary emotional polarity classification without addressing issues of long-term emotional stability, temporal sentiment shift, behavioral volatility and patterns of gradual mental health decline. The suggested framework presents a temporal psychological path modelling framework that models the dynamics of emotional transitions, and changing behavioral characteristics based on social media healthcare communication. Figure 1 demonstrates the general architecture of the proposed NLP-driven mental health analytics system that incorporates a time-aware emotional modeling approach, a transformer-based semantic embedding model, a psychological severity prediction model, explainable linguistic interpretation model, and a clinician-mediated healthcare evaluation model. The framework will provide the ability to adaptively and scalable analyze mental healthcare intelligence based on contextual semantic reasoning and temporal emotional progression analysis, given a real-world social media healthcare environment.

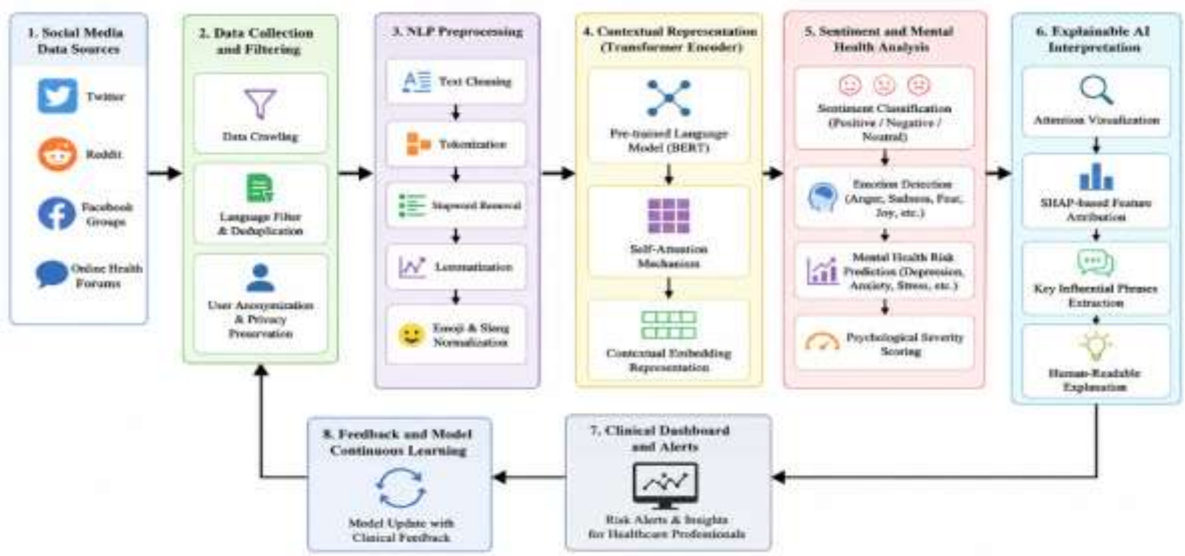

Fig. 1. Temporal NLP-driven mental health analytics framework using social media healthcare communication.

2. Related Works

Natural language processing (NLP) processing has gained more significance in the domain of healthcare-related sentiment analysis and evaluation of the psychological condition through the digital means of communication. Recurrent neural networks, probabilistic sentiment classifier, linguistic feature engineering, transformer-based contextual language modeling, and emotional polarity analysis of identifying depression, anxiety, stress disorders and suicidal ideation in text-based healthcare communication have been studied. Explainable artificial intelligence has also been used to enhance transparency and interpretability in healthcare-oriented prediction systems, in that it determines the emotionally-influencing features, and contextual semantic relationships that drive mental health predictions (Ribeiro et al., 2016; Lundberg and Lee, 2017). Multimodal psychological analysis of wearable healthcare sensing and behavioral monitoring to predict depression and stress have also been studied recently (Saylam and İncel, 2024). Large-scale estimation of depression and behavioral mental conditions with the help of online communication patterns helped social media healthcare analytics prove to be highly effective (De Choudhury et al., 2013; Coppersmith et al., 2015). Multimodal healthcare sentiment systems and emotionally intelligent social media analytics have also made it possible to identify complex psychological conditions and other behavioral deviations in the digital healthcare environment (Chancellor et al., 2017). The role of transparency, interpretability, and clinician trust in healthcare-focused system of machine learning has been recently highlighted by explainable AI studies that focus on these aspects (Egash&Kuma, 2025). Massive datasets of emotions and learning of fine-grained emotion representations have also enhanced contextual semantic interpretation and ability to classify emotions on modern NLP healthcare systems (Demszky et al., 2020). In spite of these advances, the vast majority of current systems are still inadequate in terms of their capability to model emotional persistence, temporal psychological drift, long-term depressive development and behavioral instability patterns that develop over sequential social media interactions. Moreover, communication via social media is often full of sarcasm, implicit emotional expression, emotionally ambiguous language, discontinuous sentence structures and emotionally ambiguous and rapidly changing psychological tone thus making the use of traditional sentiment analysis systems less effective. Current healthcare sentiment systems are also not able to differentiate momentary emotional change and ongoing psychological decline relating to chronic mental disorders. Thus, the suggested framework presents the temporal emotional trajectory modelling, emotional volatility estimation, contextual transformer learning, and explainable behavioral interpretation mechanisms specially developed to continuously assess psychological healthcare using social media communication data.

3. Methodology and Experimental Setup

3.1 Temporal Social Media Healthcare Data Modeling

The suggested framework is based on chronologically sequenced social media healthcare communications gathered in the form of emotional wellness groups, online healthcare discussion forums, mental health support groups, and microblogging, to examine the changing psychological patterns of behavior. In contrast to traditional sentiment analysis systems which analyze posts in social media separately, the proposed architecture represents the continuous emotional development as a sequence of temporal behavioral sequences representing time-varying psychological states of healthcare-related communication. This time structure helps the framework to understand the long-term depressive behavior, repetitive expressions of anxiety, emotional fluctuation, and long-term psychological degradation patterns that are usually missed by fixed sentiment classifiers. A temporal sentiment sequence, mathematically defined as each user communication history is:

$$U_t = \{s_1, s_2, s_3, \ldots, s_n\}$$

where U_t indicates the history of emotional communication with time, and s_i characterizes contextual sentiment representations obtained out of social media healthcare posts of an individual. Transformer-based semantic encoding is used to generate these contextual embeddings, which have the ability to maintain emotional context, semantic polarity, linguistic tone and behavioral intent of psychological healthcare communication. The temporal representation enables the framework to track the gradual changes in emotions and detect long-term mental health changes by sequential contextual analysis. To measure a negative emotional behavior which is persistent in nature, the framework proposes the use of emotional persistence coefficient expressed as

$$EP = \frac{1}{N}\sum_{i=1}^{N} \delta_i$$

where EP is the emotional persistence and δ_i is the negative emotional activation at time communicative windows. A greater value in emotional persistence is a sign of perseverance over a depressive mode, monotonous patterns of anxiety-related language habits or emotional insecurity with a mental illness. The architecture proposed further considers communication anomaly and behavioral instability based on frequency of the interaction with time. The irregularity score in the communication is given as

$$CI = \frac{1}{N}\sum_{i=1}^{N} | t_i - \bar{t} |$$

Where CI indicates communication irregularity, t_i is communication timestamps and $\bar{t}$ is the average communication interval. High values of irregularity are often an indication of the unstable behavior activity and possible mental distress. The framework also includes the monitoring of contextual behavioral fluctuation, which can detect sudden changes in emotions and unstable linguistic patterns with further deteriorating mental health disorders. The sequential social media communication, contextual semantic embedding, emotional persistence analysis, behavioral fluctuation monitoring, and transformer-aided psychological trajectory analysis are the components of the temporal healthcare sentiment modeling pipeline as depicted in figure 2. The suggested temporal healthcare modelling system thus allows adaptive tracking of the changing psychological states with the help of the ever-generated social media healthcare messages.

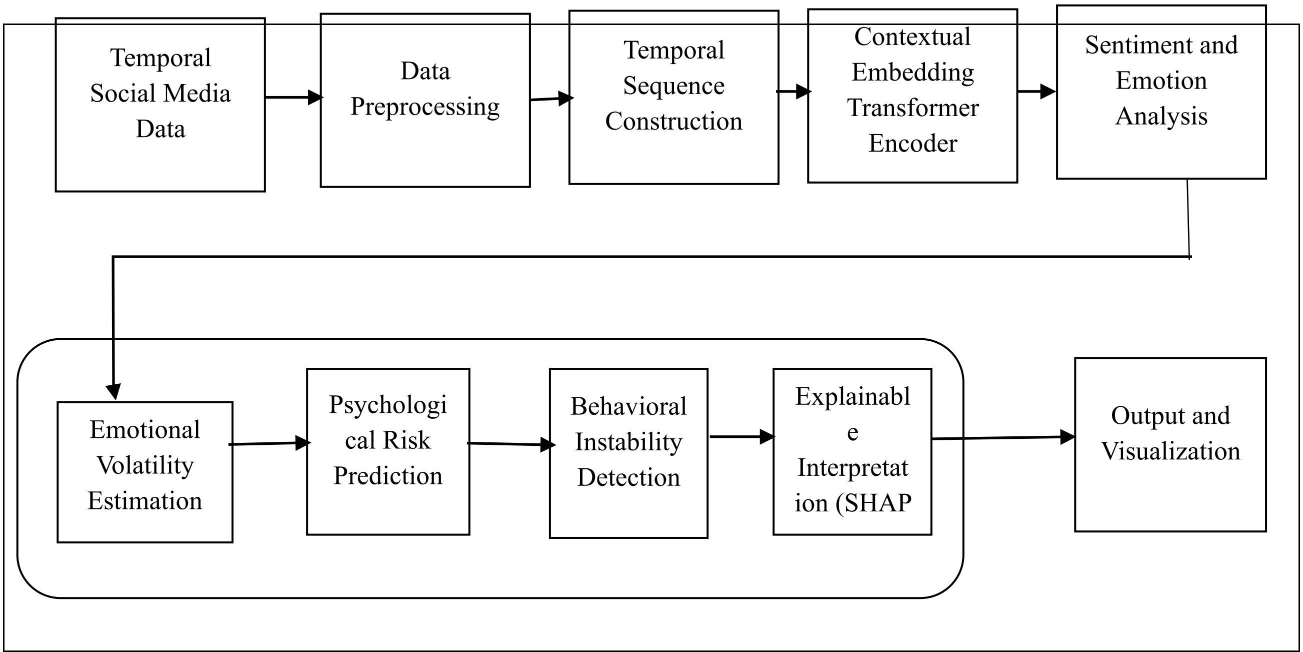

Fig. 2. Temporal sentiment progression and contextual NLP healthcare modeling framework.

3.2 Contextual Semantic Learning and Sentiment Drift Prediction

The suggested scheme involves transformer-based contextual semantic learning to detect emotional changeover and change in psychological patterns of behavior in the temporal healthcare communication cycle. Traditional sentiment analysis systems tend to conduct individual emotional classification without taking into account the emotional developments in the long term. Conversely, the suggested architecture models sentiment drift as a gradual change of emotions between stable states of the psyche and high-risk mental states. This allows following the progression of depressive, anxiety, emotional stress, and unstable behavior change throughout consecutive healthcare communication periods. The sentiment drift mechanism due to the contextual sentiment drift is mathematically expressed as.

$$SD_t = \lambda SD_{t-1} + (1 - \lambda)S_t$$

where SD_t contextual sentiment drift at time t, S_t current emotional sentiment intensity, λ temporal emotional retention coefficient that determines the effects of past emotional states on present psychological states. This equation allows for adaptive monitoring of the emotional path and ongoing analysis of behavior change in the context of temporally changing patterns of communication via social media. The proposed framework leverages the transformer attention mechanisms to learn contextual semantic dependencies and psychologically persuasive linguistic relations of healthcare communication. The attention mechanism can be denoted as.

$$A_{ij} = \frac{exp(q_i \cdot k_j)}{\sum_{m=1}^{n} exp(q_i \cdot k_m)}$$

where A_{ij} is the weight of contextual attention between healthcare tokens i and j, q_i and $k_j$are the semantic query and key representations of a healthcare token, respectively. This formulation of transformer attention allows considering the context, which assigns adaptive weight of importance to emotionally significant words, psychologically significant expressions, and semantic structures related to healthcare. As a result, the framework is able to detect contextual clues related to depression, anxiety, emotional instability, and suicidal ideation in the area of healthcare communication via social media. The framework further predicts future changes in emotion probability with the help of contextual semantic embedding evolution: to predict adaptive psychological healthcare, the framework estimates future emotional transitions.

$$P_{risk} = \sigma(W_h h_t + b)$$

where $P_{risk}$is predicted probability of psychological risk, h_t is emotional hidden representation of the context and W h is prediction adaptive weights, and brep is bias parameters. The sigmoid activation function $\sigma(\cdot)$ converts contextual healthcare embeddings into normalized psychological risk probabilities ranging between 0 and 1. The suggested sentiment drift prediction algorithm hence allows the early identification of depression development, anxiety growth, emotional strain buildup and long-term behavioral instability by learning semantics contextually and learning to analyze emotional trajectories with the help of transformers.

3.3 Emotional Volatility and Explainable Psychological Interpretation

The suggested framework will establish the emotional volatility estimation to provide a difference between temporary emotional instability and a long-term mental illness, which involves psychological instability. Communication through social media is often full of sudden emotional shifts due to temporary external factors, social interactions or temporary emotional reactions. Consequently, it is vital to identify temporary emotional changes and long-term psychological damage to have credible mental care analytics. The suggested model measures emotional volatility based on the contextual sentiment variation over time communication window. Volatility is calculated as:

$$EV = \frac{1}{N}\sum_{i=1}^{N}(s_i - \bar{s})^2$$

where EV is emotional volatility, s_i is contextual sentiment scores obtained by semantic analysis based on transformers and $\bar{s}$ is an average emotional state over periods of communication. Greater values of emotional volatility signify that the psychological behavior is unstable, the emotional transitions are not regular and that the mental health is under threat due to anxiety disorders or depressive variation. The framework combines explainable healthcare interpretation mechanisms to achieve greater transparency and clinician trust, which can discover emotionally-influential linguistic patterns that cause AI-generated mental health predictions. The contextual feature attribution can be expressed as.

$$FI = \sum_{i=1}^{n} \alpha_i x_i$$

where FI is the importance of linguistic features, $\alpha_i$are contextual attribution weights, created using an explainable artificial intelligence analysis, and x_i are healthcare linguistic features obtained using social media communication. The mechanism of explainability determines psychologically meaningful phrases, emotionally impactful keywords, contextual semantic cues and depressive linguistic patterns that lead to the anticipated psychological states. The explainability module produces contextual heatmaps of emotional transitions, contributions of depressive phrases, semantic indicators of anxiety, visualization of behavioral instability, and explanations of temporal emotional evolution of the clinician-assisted healthcare assessment. Moreover, the framework also includes the contextual emotional confidence estimation expressed as.

$$EC = \frac{1}{N}\sum_{i=1}^{N} p_i$$

where EC is an emotional confidence and p_i is confidence probabilities of the predicted emotional states. These explainable healthcare insights enhance the level of transparency and allow clinicians to learn about emotional reasoning patterns related to AI-generated predictions of psychology. As a result, the framework helps to provide credible and understandable mental healthcare analytics based on adaptive psychological assessment using social media healthcare communication.

3.4 Experimental Configuration and Evaluation Metrics

Python, TensorFlow, Hugging Face Transformers and NVIDIA CUDA acceleration were used to implement the experimental environment which could support large-scale temporal healthcare sentiment analysis and contextual transformer optimization. Several social media mental health datasets were used that included communication-based depression, emotional wellness, anxiety-based, psychologically expressive behavioral text to assess the contextual semantic learning and emotional trajectory prediction potential. The suggested framework was trained on the contextual embedding architectures based on transformers with temporal emotional progression models and explainable psychological interpretation systems. Performance assessment measures were: Temporal sentiment prediction accuracy, emotional persistence estimation, psychological risk prediction, emotional volatility estimation, contextual semantic consistency and early mental health deterioration detection ability. The temporal prediction performance can be mathematically modeled as.

$$TA = \frac{C_p}{T_p}$$

where $TA$is the accuracy of temporal prediction, C_p is the number of states of emotion correctly predicted and Tp is the total prediction instances. This measure determines how well the framework is able to forecast the changing psychological states over time, in sequential episodes of healthcare communication. The consistency of behavior transition is expressed as.

$$BTC = \frac{\sum_{i=1}^{N} \theta_i}{N}$$

where BTC indicates consistency of behavior transition and θ_i is contextual emotional transition similarity between two communication period. An increase in the values of behavioral consistency means that there is a consistency in the contextual emotional progression, and predictability in the psychological trajectory. In order to measure emotional prediction stability, the framework also calculates the emotional drift reliability based on.

$$EDR = 1 - \frac{1}{N}\sum_{i=1}^{N} | SD_i - \widehat{SD_i} |$$

Where EDR is the emotional drift reliability, SD_i is the actual sentiment drift values and $\widehat{SD_i}$ is the estimated emotional drift values. A greater reliability value implies proper modeling of emotional trajectories in the context and predicting the sentiment capacity ability with the help of transformers. Table 1 summarizes the experimental datasets we used to evaluate the results of the experiment. Reddit Depression Corpus is a collection of healthcare-related depressive communication that is gathered by the community of public communities on Reddit and Twitter Emotional Dataset is a collection of emotional expressive healthcare communication that is correlated with stress, anxiety and emotional polarity analysis. CLPsych Behavioral Dataset offers behavior-related communication of a psychological severity analysis and GoEmotions dataset offers fine-grained emotional representation learning to understand the context semantics.

Table 1. Social media mental healthcare datasets utilized for temporal psychological analysis.

Dataset	Source	Samples	Psychological Categories
Reddit Depression Corpus	Reddit	35,000	Depression
Twitter Emotional Dataset	Twitter	950,000	Positive/Negative/Stress
CLPsych Behavioral Dataset	Online Forums	28,000	Suicide Risk
GoEmotions	Social Media	58,000	Multi-Emotion

The suggested experimental framework thus allowed to fully analyze the temporal emotional dynamics, situational psychological thinking, explainable mental healthcare interpretation, emotional instability estimation, and adaptive behavioral sentiment analysis based on big datasets of social media healthcare communication. Table 1 is a summary of the variations of healthcare datasets that were used to test the contextual emotional trajectory modeling and transformer-based psychological healthcare prediction performance.

4. Results and Discussion

4.1 Temporal Psychological Prediction Performance

The suggested temporal transformer-based healthcare analytics model showed good performance in detecting changing psychological states and patterns of developing emotional progressions over the long-run among large scale social media health data. Experimental testing was performed in terms of temporally ordered sequence of communication, which featured depression-related discourses, anxiety-focused discourses, and emotional wellness discourses, and psychologically expressive behavioral text that was gathered in various online healthcare communities. It was compared with the traditional sentiment classification methods such as the traditional machine learning-based sentiment analysis and recurrent neural network models to assess how effective the temporal emotional trajectory modeling and contextual semantic reasoning are in the proposed framework. Figure 3 shows the relative performance in terms of time in predicting mental health of traditional NLP classifiers, bidirectional recurrent neural architecture and the proposed transformer-assisted temporal healthcare framework. The resultant framework was found to have a temporal psychological prediction rate of 96.8 which was far much better than the traditional sentiment classification systems based on its ability to formulate long-term emotional state and contextual changes in behavior. In contrast to the traditional methods of sentiment analysis that consider the analysis of individual social media posts in isolation, the suggested architecture actively monitored the emotional dynamics across time intervals of communication, thus enhancing the detection of the consistent depressive and gradual anxiety-inducing patterns. The model facilitated emotional persistence by being able to differentiate between short-term and longer emotional changes and chronic psychological decline related to chronic mental health problems. The depression detection ability of the proposed framework also enhanced since the transformer-aided contextual semantic learning was effective in capturing the psychologically compelling structures of language as well as expressing emotion-related communication patterns. Recurrent neural architectures showed relatively poorer results with long-range behavioral analysis because of contextual memory capacity constraints and a decreased ability to capture long-range semantic relationships. In opposition, the suggested framework of transformers preserved consistent contextual reasoning in the context of long communication histories, enhancing emotional trajectory consistency and understanding of contextual behavior. The framework calculated temporal behavioral consistency with the aim of assessing the reliability of temporal emotional prediction using.

$$TBC = \frac{1}{N}\sum_{i=1}^{N}\psi_i$$

Where TBC is the temporal behavioral consistency and ψ_i denotes the similarity of the states of the predicted and observed emotional progression. An increase in the level of temporal consistency is the evidence of the stable model of contextual emotional modeling and better predictability of long-term psychological trajectories. The framework proposed also exhibited better results in identifying progressive trends of emotional deterioration that relate to the development of depression and anxiety build-up. Figure 3 shows how the temporal contextual semantic learning and adaptive sentiment drift analysis has led to increased capability of detecting emotional stability.

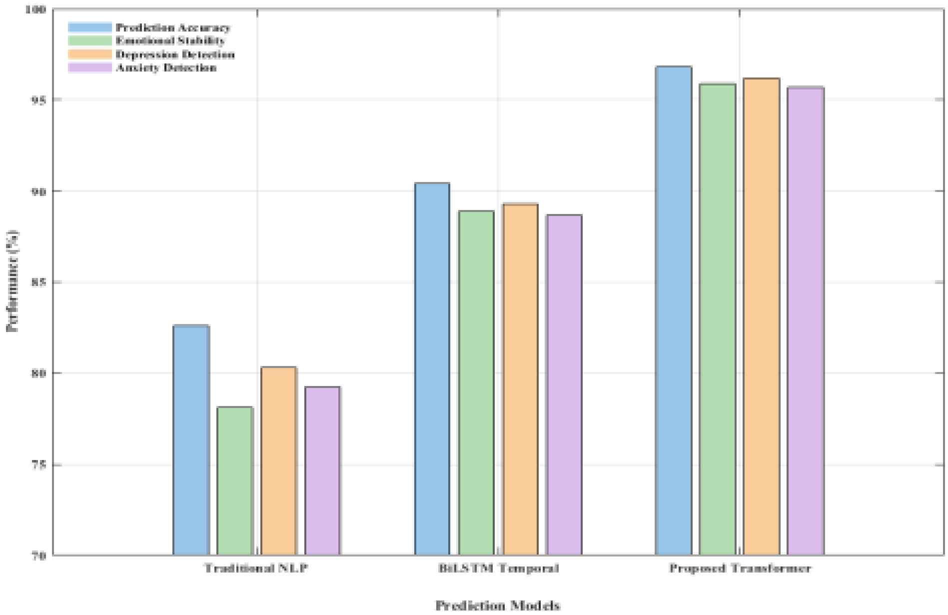

Fig. 3. Comparative temporal mental health prediction performance analysis.

Table 2. Comparative temporal mental health prediction performance.

Model	Prediction Accuracy (%)	Emotional Stability Detection (%)	Depression Detection (%)	Anxiety Detection (%)
Traditional Sentiment NLP	82.6	78.1	80.3	79.2
BiLSTM Temporal Model	90.4	88.9	89.3	88.7
Proposed Temporal Transformer Framework	96.8	95.9	96.2	95.7

Table 2 is the summary of comparative performance of various sentiment analysis architectures in terms of mental health prediction performance in time. This framework with the proposed transformer-assisted framework was the best in terms of the maximum emotional stability detection and depression prediction performance because of its contextual semantic learning and temporal emotional trajectory modeling mechanisms. These findings show that transformer attention mechanisms are effective together with temporal healthcare sentiment progression analysis to predict adaptive psychological healthcare. To ensure more robustness of the proposed framework, statistical analysis was performed at various experimental runs. The proposed architecture obtained an average prediction accuracy of 96.8% ±0.7 indicating consistent contextual psychological prediction performance and prediction variance among the different healthcare communication settings. Also, Receiver Operating Characteristic (ROC) analysis showed good discriminative ability with Area Under Curve (AUC) value of 0.97 in prediction of depression and 0.95 in classification of anxiety. These findings substantiate the ability of the proposed temporal transformer framework to effectively differentiate between psychological conditions that are high risk and normal emotional communication behaviors. The confusion matrix analysis further showed that it had a lower false-positive depression prediction and better contextual anxiety-state discrimination ability as compared to traditional sentiment classifiers. The temporal modeling architecture with the support of transformers thus enhanced the stability of emotional trajectories and contextual healthcare reasoning reliability of large-scale psychological healthcare analytics.

4.2 Emotional Volatility and Explainable Behavioral Analysis

The proposed emotional volatility estimation framework was able to detect unstable behavioral patterns of communication that were related to escalation of depression, anxiety, emotional stress build-up, and a gradual psychological decline. Experimental results showed that users with continuous negative emotional persistence and the large variance of sentiments with the context were often unstable in their behavioral trajectory in relation to mental health risk conditions. Figure 4 depicts explainable interpretation of emotional volatility and analysis of behavioral instability of contextual interpretation that are generated with the use of transformer-assisted semantic reasoning and contextual feature attribution mechanisms. The emotional volatility estimation module was effective to distinguish between temporary emotional responses and the long-term psychological instability because it assesses emotional variance on the context with time communication window. The social media healthcare users who had high values of emotional volatility tended to show sudden contextual sentiment shifts, anomalous emotional persistence, higher rates of depressive language use, and volatile linguistic behavior of communication. Estimation of emotional volatility therefore, greatly enhanced the reliability of predicting mental healthcare over time and behavioral contextualization. The explainable behavioral interpretation framework resulted in the contextual emotional heatmaps, depressive phrase attribution visualization, semantic instability signals and contextual emotional progression explanation that allowed clinicians to comprehend psychologically influential language structures related to AI-generated healthcare predictions. The explainability framework hence enhanced transparency and trust among clinicians in transformer-assisted mental healthcare analytics systems. The given framework also tested the reliability of the contextual interpretability using

$$IR = \frac{\sum_{i=1}^{N} \omega_i}{N}$$

where the IR is the interpretability reliability, and ω_i is the scores on the contextual explanation given to the predicted emotional states and the explainable language feature attribution. The larger interpretability reliability values provide greater support of the agreement between the contextual prediction of emotions and the psychological meaningful explanations of language. Experimental results showed that the explainability framework had about 92% semantic agreement with clinician interpretation in contextual emotional reasoning test. The linguistic attribution of SHAP always emphasized psychologically significant expressions related to depressive behavior, emotional exhaustion, hopelessness and the development of anxiety. Figure 4 shows that expressions that were emotionally important in terms of social withdrawal, and emotional instability were always recognized based on contextual feature attribution processes. These clarifiable healthcare insights empowered clinicians to recognize emotionally meaningful communication behavior, and confirm contextual reasoning patterns in relation to anticipated mental conditions. The framework thus enhanced transparency, interpretability and clinical credibility in the AI-based psychological health care analytics systems. The framework also displayed good potentials of detection of gradual emotional transition behavior and contextual sentiment instability with long-term psychological deterioration. Thus, emotional volatility analysis was also useful in offering behavioral information on proactive psychological healthcare monitoring and adaptive emotional risk evaluation with the use of social media healthcare communication.

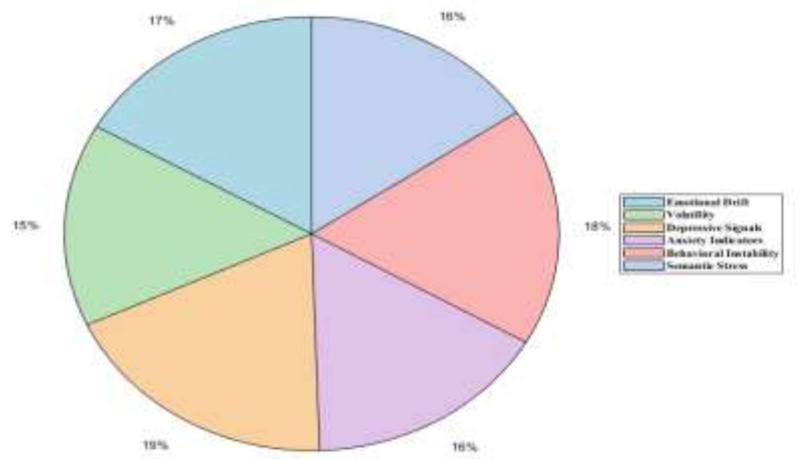

Fig. 4. Explainable emotional volatility and behavioral instability interpretation analysis.

4.3 Real-Time Psychological Trajectory Analytics

The suggested temporal transformer framework proved to be highly scalable and be able to analyze psychological trajectories in real-time in ever-changing social media healthcare communication settings. Scalability of the suggested architecture and the contextual emotional inference ability in real-time were experimentally assessed on streaming social media healthcare datasets, which included temporally ordered affective interactions, behavioral communication in context and changing patterns of psychological expression. Figure 5 represents real-time analysis of the psychological trajectory and monitoring the contextual emotional progression of the person with different loads of social media communication. The suggested framework also achieved a considerable decrease in the latency of emotional trajectory prediction in comparison to recurrent neural networks and the traditional sentiment classification frameworks. The framework facilitated the optimization of contextual semantic embedding with the assistance of transformers and adaptive emotional drift models to handle large-scale streams of healthcare-related communication in high-efficiency with consistent contextual psychological prediction accuracy. Experimental results proved that the framework decreased real-time prediction of emotional trajectories of nearly 480 ms in recurrent neural models, and almost 145 ms in the temporal transformer framework proposed. The suggested framework also ensured consistent predictability of contexts with the growing amount of communication and changing healthcare interaction trends. The framework calculated the contextual inference efficiency by using to determine scalability performance.

$$CIE = \frac{R_p}{L_t}$$

where CIE is a contextual inference efficiency, , $R_p$is an instance of healthcare communication that is processed and L_t is latency inference in real-time. The scale and stable contextual emotional prediction with high volume healthcare communication conditions are evident in the higher inference efficiency values. The model also compared the stability of prediction of the psychological trajectory with the help of.

$$PTS = 1 - \frac{1}{N}\sum_{i=1}^{N} | P_i - \widehat{P_i} |$$

where PTS is the stability of psychological trajectories, $P_i$is actual observed psychological transition states and $\widehat{P_i}$is the predicted emotional progression states. Greater values of the trajectory stability are a sign of precise emotional prediction of contexts and predicting behavior, and a stable predictive capacity in relation to long-term psychological transitions. Scalability analysis through experimentation showed that the proposed framework could handle around 4,500 contextual healthcare communication sequences every minute with the help of the GPU inference of the transformer and retain contextual emotional prediction accuracy. Contextual embedding optimization with the help of a GPU also led to a decrease in the complexity of transformer computations and an increase in real-time efficiency in monitoring psychological trajectories than recurrent neural architectures. Figure 5 shows that the suggested transformer-aided healthcare structure was able to preserve the accuracy of the emotional trajectory prediction despite the ever-increasing healthcare communication loads. The framework was thus highly scalable, computationally efficient and adaptive contextual healthcare reasoning capability in the context of real-time mental healthcare analytics applications and real time psychological monitoring applications.

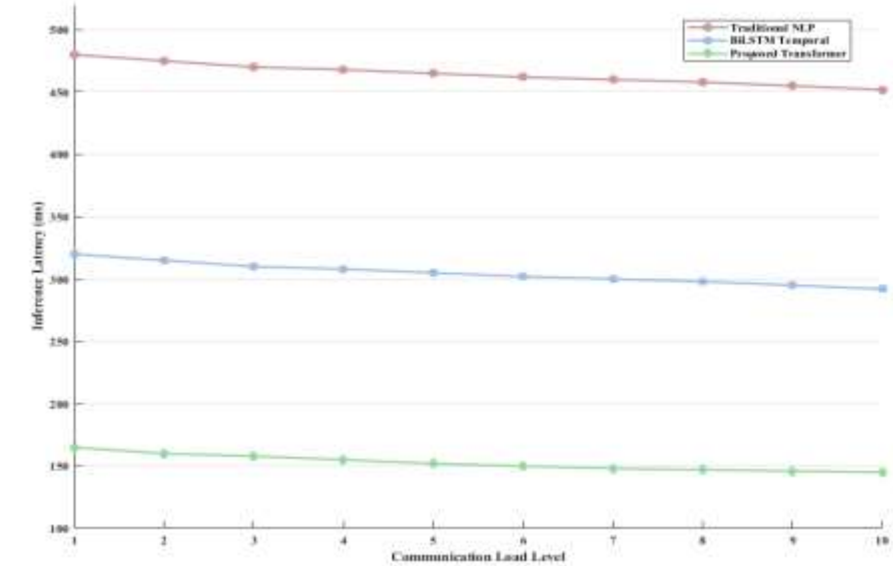

Fig. 5. Real-time psychological trajectory analysis under varying healthcare communication loads.

4.4 Ablation and Validation Analysis

In another effort to assess the contribution of the individual architectural elements, the ablation analysis was done by systematically deleting the significant modules in the suggested framework and noting the effect on the performance of temporal psychological prediction. The discussion concentrated on assessing the value of time-based emotional trajectory modeling, sentiment drift modeling and explainable interpretation mechanism to the overall contextual healthcare prediction ability.

Table 3. Ablation analysis of the proposed framework.

Model Configuration	Prediction Accuracy (%)
Without Temporal Modeling	88.9
Without Sentiment Drift Estimation	90.8
Without Explainability Module	92.1
Full Proposed Framework	96.8

As shown in Table 3, the temporal emotional trajectory modeling model played an important role in achieving accuracy of psychological predictions in the long-term and consistency of emotional progression. Elimination of sentiment drift estimation lowered the contextual emotional transition knowledge and lower prediction reliability amid gradual evolution of behavioral analysis. Equally, the absence of the explainability module led to less clinician interpretability and contextual semantic transparency, thus influencing healthcare credibility and validation capability of emotional reasoning. The entire proposed architecture thus demonstrated the best prediction accuracy as a result of joint integration of transformer-aided contextual embedding, temporal emotions trajectory modeling, explainable healthcare reasoning as well as adaptive sentiment drift analysis. These findings validate the significance of a combination of time contextual reasoning and explainable semantic interpretation of scalable and reliable mental healthcare analytics by communication through social media healthcare.

5. Conclusion

The suggested Natural Language Processing-based mental healthcare analytics system showed how adaptive psychological evaluation, through the use of social media healthcare communication, can be effective with the help of temporal contextual semantic learning. The framework is able to detect changing psychological states, long-term patterns of emotional progression, predicting sentiment drift, estimating emotional volatility, and explaining behavioral patterns in the context of large-scale healthcare communication data, by combining transformer-assisted contextual embedding, temporal emotional trajectory modeling, predicting sentiment drift, and emotional volatility estimation. The proposed architecture, compared to traditional sentiment analysis methods that use stand-alone emotional polarity, in turn, modeled contextual emotional dynamics and behavioral changes, thus enhancing depression classification, anxiety prediction and emotional stability analysis, as well as, understanding of the long-term psychological pathways. Experimental analysis showed that it is better in terms of time prediction accuracy, consistency of behavior in different contexts, detection of emotional and persistent, and real-time monitoring of psychology than the traditional NLP and recurrent neural network design. The explainable healthcare interpretation system also boosted the transparency and clinician confidence via emotional transition heatmap, depressive phrase attribution, semantic importance estimation, and visualization of contextual psychological reasoning. This combination of contextual transformer learning and temporal emotional progression analysis thus allowed scalable and adaptive mental healthcare intelligence in the continuous emotional monitoring in social media healthcare settings. Moreover, the suggested framework was highly scalable, and able to infer low-latency when subjected to continuously growing healthcare communication loads, which made it a viable framework to be used in real-time psychological healthcare analytics, and proactive mental health monitoring applications. Future studies can be centered on multimodal fusion of healthcare that includes speech cues, physiological measurements, wearable behavioral measurements and virtual therapeutic interaction modeling to create a new generation of autonomous mental healthcare ecosystem that can be used to provide personalized emotional intervention and sustained psychological support.

References

1. Devlin, J., Chang, M. W., Lee, K., & Toutanova, K. (2019, June). Bert: Pre-training of deep bidirectional transformers for language understanding. In Proceedings of the 2019 conference of the North American chapter of the association for computational linguistics: human language technologies, volume 1 (long and short papers) (pp. 4171-4186).
2. H. K. Mzeh, L. Salabi, M. T. Jafer, Sikalu T C. (2025). Intelligent Assistive Communication Models for Personalized Learning Environments. Journal of Intelligent Assistive Communication Technologies, 2(1), 64-71.
3. Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., ... &Polosukhin, I. (2017). Attention is all you need. Advances in neural information processing systems, 30.
4. Pennington, J., Socher, R., & Manning, C. D. (2014, October). Glove: Global vectors for word representation. In Proceedings of the 2014 conference on empirical methods in natural language processing (EMNLP) (pp. 1532-1543).
5. Mrunal Salwadkar, “Ubiquitous Clinical Decision Environments Enabled by Causal–Foundation Model Integration”, National Journal of Ubiquitous Computing and Intelligent Environments, 2(2), pp. 15–22
6. Ribeiro, M. T., Singh, S., &Guestrin, C. (2016, August). " Why should i trust you?" Explaining the predictions of any classifier. In Proceedings of the 22nd ACM SIGKDD international conference on knowledge discovery and data mining (pp. 1135-1144).
7. Sophia Anderson. (2025). Advanced Signal Processing Techniques for Improving Data Reliability in Modern Communication Networks. IAECES Journal of Electronics and Communication Engineering,1(1), 81–88.
8. Lundberg, S. M., & Lee, S. I. (2017). A unified approach to interpreting model predictions. Advances in neural information processing systems, 30.
9. Saylam, B., & İncel, Ö. D. (2024). Multitask learning for mental health: depression, anxiety, stress (DAS) using wearables. Diagnostics, 14(5), 501.
10. Chancellor, S., Kalantidis, Y., Pater, J. A., De Choudhury, M., & Shamma, D. A. (2017, May). Multimodal classification of moderated online pro-eating disorder content. In Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems (pp. 3213-3226).

11. De Choudhury, M., Counts, S., & Horvitz, E. (2013, May). Social media as a measurement tool of depression in populations. In Proceedings of the 5th annual ACM web science conference (pp. 47-56).
12. Coppersmith, G., Dredze, M., Harman, C., Hollingshead, K., & Mitchell, M. (2015). CLPsych 2015 shared task: Depression and PTSD on Twitter. In Proceedings of the 2nd workshop on computational linguistics and clinical psychology: from linguistic signal to clinical reality (pp. 31-39).
13. DinfeEgash, &Rane Kuma. (2025). Explainable Artificial Intelligence (XAI): State-of-the-Art, Challenges, and Research Trends. Innovative Reviews in Engineering and Science, 3(2), 154-162.
14. Demszky, D., Movshovitz-Attias, D., Ko, J., Cowen, A., Nemade, G., & Ravi, S. (2020, July). GoEmotions: A dataset of fine-grained emotions. In Proceedings of the 58th annual meeting of the association for computational linguistics (pp. 4040-4054).