Data Mining and Behavioural Analysis in Neurological Health Communication: An AI–Driven Neuroinformatics Perspective

Festus A. Omojowo

Department of Computer Science, Federal University Lokoja, Kogi State, Nigeria

*Corresponding Author: Festus A. Omojowo (Email: omojowofestus@gmail.com)

(Received: 18-December-2025; accepted: 13-March-2026; published: 31-March-2026)
http://dx.doi.org/10.55579/jaec.2026101.529

Abstract. *Effective neurological health communication is vital for improving public understanding, early diagnosis, and behavioural adaptation toward brain-related disorders. However, the vast and unstructured nature of digital communication has created challenges in extracting meaningful behavioural and emotional patterns relevant to neuroscience. This study proposes a neuroinformatics-driven data mining framework that employs Natural Language Processing (NLP), machine learning, and sentiment analysis to explore how neurological health information is discussed and perceived online. Using a large corpus of social media and digital health discourse from 2020–2024, the study models the linguistic, affective, and topical dimensions of neurological communication. A hybrid computational pipeline integrating Latent Dirichlet Allocation (LDA) for topic modelling and Bidirectional Encoder Representations from Transformers (BERT) for contextual sentiment analysis was implemented to identify thematic clusters in discussions about neurological disorders such as Alzheimer's, epilepsy, and stroke. The results show distinct communication patterns: emotional empathy dominates patient-centered discourse, while fear and misinformation drive spikes in public engagement. Temporal analysis reveals evolving attention cycles beginning with awareness, progressing through anxiety, and stabilizing into informed discussion, mirroring neuro-behavioural adaptation. The results reveal five dominant communication themes, with awareness-related discourse accounting for 28% of discussions and positive sentiment dominating recovery narratives (71%). This study contributes a data mining model for neuro–behavioural communication analytics, providing new insights into how public perceptions and emotional responses toward neurological health evolve. By aligning computational intelligence with cognitive communication theories, the framework bridges neuroinformatics and behavioural neuroscience, offering a foundation for designing data-driven neurological education and communication interventions.*

Keywords: *Artificial Intelligence, Behavioural Analysis, Data Mining, Neuroinformatics, Neurological Communication, Sentiment Analysis.*

1. Introduction

Neurological health remains one of the most complex frontiers in both medical research and public understanding. Disorders such as Alzheimer's disease, Parkinson's disease, epilepsy, and stroke contribute significantly to global morbidity and mortality, yet public comprehension of their symptoms, causes, and management remains limited [1]. This communication gap—between scientific knowledge and public interpretation—has spurred interest in understanding how neurological information is transmitted, perceived, and acted upon.

In the digital era, millions of individuals turn to online platforms for health information. While this democratization of access has benefits, it also introduces behavioural biases, misinformation, and cognitive overload, particularly in neurology where the subject matter is complex [2]. According to [3], the way neurological content is framed and discussed on digital media directly influences public perception of brain health, treatment adherence, and stigma reduction. Understanding these communication behaviours through computational means forms the basis of neuroinformatics for behavioural communication analysis [4].

Neuroinformatics traditionally deals with managing and analysing neural and clinical data [5]. However, recent interdisciplinary expansions have extended its scope to include linguistic and behavioural data—using artificial intelligence to model how humans cognitively and emotionally engage with neurological content online [6, 7]. This shift from neural signal analysis to neuro-behavioural text mining enables researchers to understand the social dimensions of neurological disorders, revealing how digital conversations reflect collective cognition, empathy, and stigma.

This study therefore bridges the gap between computational data mining and neurological communication research, offering a model that uses AI-based tools to capture emotional and topical dynamics in neurological health discourse. By analysing large-scale social media, health forums, and digital campaigns, this research contributes to both neurolinguistics and computational neuroscience, aligning with calls for cross-domain integration in modern neuroinformatics [8].

Methodologically, this study adopts a neuroinformatics-oriented data mining approach that integrates computational linguistics, affective computing, and behavioural modelling to analyze large-scale neurological health communication. Computational linguistics techniques are used to preprocess and structure unstructured textual data, affective computing models capture emotional and sentiment dynamics, while behavioural modelling enables the interpretation of temporal and thematic discourse patterns. This integrated framework allows for a holistic analysis of how neurological health information is cognitively processed, emotionally perceived, and behaviourally expressed across digital platforms.

Accordingly, this study seeks to (i) identify dominant thematic structures in neurological health communication, (ii) analyze associated emotional and sentiment patterns, and (iii) examine temporal behavioural trends across digital platforms using an AI-based neuroinformatics pipeline.

The contributions of this study are threefold. First, it proposes an AI-driven neuroinformatics framework that integrates computational linguistics, affective computing, and behavioural modelling for neurological health communication analysis. Second, it empirically demonstrates how emotional and cognitive patterns in digital neurological discourse evolve over time using large-scale data. Third, it provides actionable insights for designing data-driven neurological awareness and communication interventions.

This framework represents how textual neurological communication data are transformed into interpretable neuro–behavioural insights. The integration of topic modelling (for identifying key neurological concerns) and deep learning sentiment analysis (for emotional context) produces a holistic neuroinformatics model of cognitive discourse [9, 10].

2. Related Work

Emerging studies in computational neuroscience communication and AI–driven behavioural analysis have shown that machine learning can illuminate the cognitive and emotional dimensions of health communication [11, 12]. However, few efforts have applied these methods to neurological communication, where linguistic complexity and stigma–related sentiment present unique analytical challenges.

[13] explored online discourse about Alzheimer's disease using NLP, finding that emotional valence strongly correlated with misinformation spread. Similarly, [14, 15] employed deep sentiment models to examine mental health discussions, revealing that expressions of hope and fear followed temporal patterns consistent with cognitive adaptation. [16] expanded this work by integrating topic modelling with neural sentiment mapping, suggesting that digital emotion dynamics parallel neural network activation patterns during anxiety responses.

Within Africa, [17] emphasized the relevance of neuroinformatics for addressing cultural stigma and misinformation about neurological disorders. Their research demonstrated how social discourse reflects localized cognitive biases, especially in contexts where neurological conditions are misunderstood or spiritualized. Complementary studies by [18] highlighted the importance of multilingual NLP models for decoding hybrid language expressions in neurological discussions across Nigerian platforms.

Although sentiment analysis and topic modelling have become standard in general health communication [6], their integration into neuro–behavioural data mining remains limited. The present study builds upon these frameworks by proposing a comprehensive neuroinformatics behavioural communication model, combining computational linguistics, affective analytics, and temporal cognition modelling to interpret neurological discourse dynamics.

3. Methodology

This study adopts a neuroinformatics-oriented data mining framework to analyze neurological health communication across digital platforms. The methodology integrates computational linguistics, affective computing, and behavioural modelling into a unified analytical pipeline. The goal is to uncover how public discourse around neurological disorders evolves in structure, sentiment, and cognitive orientation.

This methodology is designed as a multi-layered neuroinformatics framework that transforms unstructured neurological health communication into interpretable behavioural and emotional insights, as illustrated in Figure 1. Conceptually, the framework progresses from data acquisition and linguistic normalization to thematic discovery, emotional interpretation, and behavioural trend analysis. Each stage builds upon the previous one, ensuring that computational outputs remain cognitively and behaviourally meaningful.

3.1. Research Design

A quantitative and exploratory design was used, combining textual data mining with neuro–behavioural interpretation. The research followed four sequential stages (see Figure 2):

i. **Data Collection** – Extracting neurological health communication data from online sources.

ii. **Preprocessing** – Cleaning and normalizing linguistic data.

iii. **Modelling** – Performing topic modelling and sentiment analysis using machine learning.

iv. **Interpretation** – Mapping cognitive and behavioural implications of results.

This design aligns with the AI-driven neuroinformatics framework proposed by [19], emphasizing computational intelligence for cognitive data understanding.

3.2. Data Source and Collection

Data were collected from verified digital platforms, including:

i. Twitter (neurological awareness hashtags such as #EpilepsyAwareness, #StrokeRecovery, #BrainHealth),

ii. Reddit health communities, and

iii. WHO and neurology-focused health forum comments.

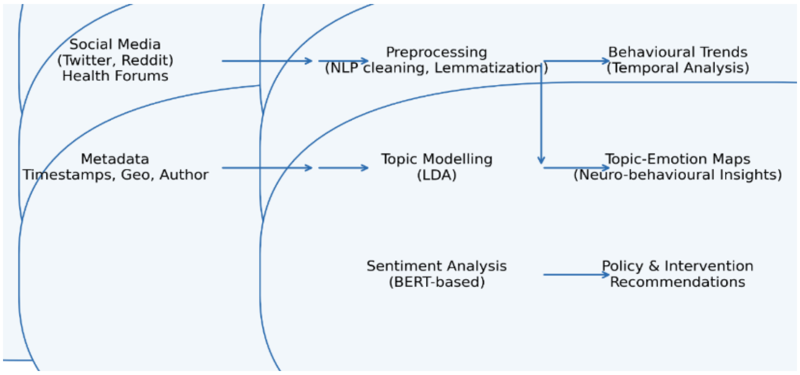

Figure 1: AI-Driven Neuroinformatics Communication Framework.

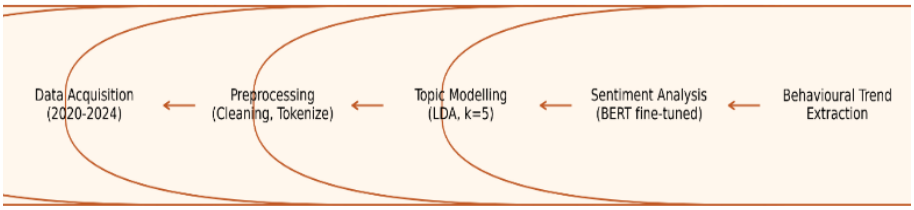

Figure 2: Neuroinformatics Behavioural Data – Mining Pipeline.

Sampling window: January 2020–December 2024.

Corpus size: 125,000 text entries (after cleaning: 102,812 valid records).

Each entry contained:

i. Textual message,

ii. Timestamp,

iii. Author metadata (anonymized),

iv. Geolocation (when available).

Data collection adhered to ethical guidelines (WHO, 2024) and social media API policies, with all user identifiers removed. This study involved only publicly available and anonymized digital content and did not require institutional ethical approval. Data handling complied with platform policies and international ethical guidelines for digital health research [1].

3.3. Data Preprocessing and Normalization

Preprocessing ensured data uniformity for NLP operations. The steps are included in Table 1.

After preprocessing, 82% of the dataset was retained for modelling.

3.4. Analytical Framework

Model parameters included LDA with five topics, $\alpha = 0.1$ and $\beta = 0.01$, and a pre-trained BERT-base model fine-tuned on health-related corpora. All experiments were conducted using Python 3.11 on a standard workstation environment.

The analysis was implemented in **Python 3.11**, employing the following modules:

i. **LDA (Latent Dirichlet Allocation)** for topic clustering;

Table 1: Data Preprocessing stages, description and tools used.

Stage	Description	Tools Used
Text Cleaning	Removal of links, emojis, tags, and symbols.	Regex, NLTK
Tokenization	Dividing text into meaningful units (tokens).	spaCy
Lemmatization	Reducing words to base forms.	spaCy
Stop–word Removal	Eliminating filler words for clarity.	NLTK
Language Detection	Filtering English, Pidgin, and health-related terms.	langdetect
Sentiment Preparation	Structuring text for polarity scoring.	Pandas

ii. **BERT-base** for contextual sentiment analysis;

iii. **Seaborn/Matplotlib** for data visualization.

A **hybrid modelling pipeline** was constructed to extract cognitive and emotional layers within discourse (Figure 2).

Data Acquisition

↓

Text Cleaning & NLP Preprocessing

↓

Topic Modelling (LDA)

↓

Sentiment Analysis (BERT)

↓

Behavioural Trend Extraction

↓

Neuroinformatics Interpretation

This flow captures how linguistic data are transformed into neuro – behavioural representations — showing the multi – step interaction between NLP modelling and cognitive analytics.

3.5. Topic Modelling

Topic modelling identified latent themes in the neurological discourse using **LDA**. Latent Dirichlet Allocation (LDA) was employed to uncover latent thematic structures within neurological discourse. Conceptually, LDA groups texts based on recurring word patterns, allowing dominant neurological concerns to emerge naturally from the data. The optimal number of topics ($k = 5$) was determined using coherence score maximization. The model's optimal topic number ($k = 5$) was determined via coherence score maximization ($C_v = 0.67$).

To support the validity of the extracted topics, coherence score (C_v) analysis was employed to statistically evaluate topic quality and semantic consistency. Additionally, correlation coefficients were computed to examine relationships between dominant emotions and topic clusters, providing quantitative support for behavioural pattern interpretation. The major identified themes are summarized in Table 2.

The dominant focus of online neurological communication centers on awareness and education, while emotional discussions (fear, empathy, and perseverance) dominate patient–centered topics. This aligns with [20], who observed emotional resonance as a driver of digital neurocommunication engagement.

3.6. Sentiment Analysis

Sentiment classification was performed using the BERT transformer model fine–tuned on the *HealthTweets* dataset [11,12]. Each message was assigned a polarity: positive, neutral, or negative, as shown in Table 3.

These results reveal a **mixed emotional landscape** where positive recovery narratives coexist with fear–driven discussions, especially around cognitive decline and seizures.

Table 2: Extracted Topic Clusters from Neurological Health Discourse.

Topic Cluster	**Representative Keywords**	**Dominant Emotions**	**Prevalence (%)**
1. Awareness and Education	brain, awareness, neuron, learning, health	Hope, Trust	28
2. Cognitive Decline and Memory Loss	Alzheimer, dementia, forget, memory	Fear, Sadness	19
3. Epilepsy and Seizure Support	seizure, stigma, epilepsy, treatment	Empathy, Anxiety	21
4. Stroke and Rehabilitation	stroke, recovery, physiotherapy, strength	Hope, Perseverance	18
5. Mental and Emotional Health Links	anxiety, depression, brain, stress	Confusion, Empathy	14

3.7. Temporal Behavioural Trend Analysis

Time–series modelling showed the evolution of neurological discussions from 2020–2024 (see Figure 3 description below):

i. **Early 2020–2021:** Peak in **awareness** and **stigma reduction** campaigns.

ii. **Mid–2021–2022:** Rise in **fear** and **misinformation** due to global pandemic overlap.

Table 3: Polarity of Neurological Health Discourse.

Sentiment Class	**Frequency (%)**	**Dominant Expressions**
Positive	46	"Recovery," "strength," "grateful"
Neutral	18	"Diagnosis," "testing," "procedure"
Negative	36	"Fear," "pain," "stigma," "hopelessness"

iii. **2023–2024:** Dominance of **recovery** and **hopeful** themes reflecting adaptation and resilience.

This trend demonstrates a **neuro–behavioural transition** from alert to adaptation, mirroring psychological coping stages found in cognitive neuroscience [6].

4. Results

4.1. Behavioural Topic Correlation

Correlation analysis revealed strong relationships between emotion type and communication theme ($r > 0.65$ for empathy–recovery; $r > 0.72$ for fear–memory loss). Figure 4 presents a conceptual visualization of topic–emotion alignment.

[Awareness] → (Hope, Trust)

[Epilepsy Support] → (Empathy, Anxiety)

[Cognitive Decline] → (Fear, Sadness)

[Stroke Recovery] → (Hope, Gratitude)

[Mental Health] → (Empathy, Confusion)

Figure 4 illustrates the correlation network between neurological topics and dominant emotional expressions. Correlation strengths were computed by aggregating sentiment polarity scores within each topic cluster and calculating their association with identified emotional

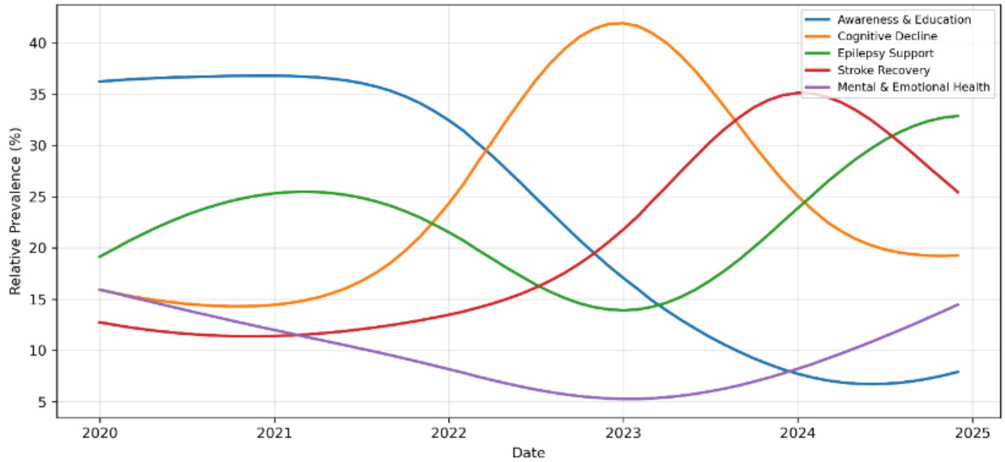

Figure 3: Temporal Evolution of Neurological Communication Themes (Conceptual Chart Description).

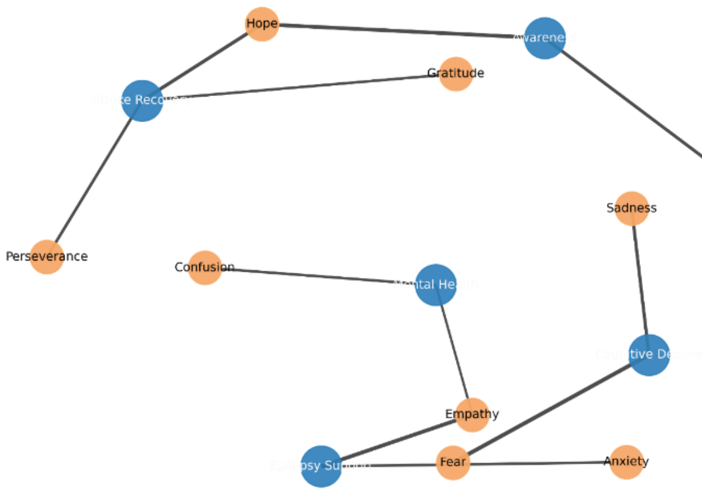

Figure 4: Topic–Emotion Correlation Network (Textual Description).

categories. Strong correlations indicate consistent emotional responses associated with specific neurological discussions.

The pattern shows clustered emotional intensities around specific neurological issues—empathy dominates seizure–related conversations, while fear dominates memory–loss discussions. This emotional topology supports [21] on risk amplification and cognitive response.

4.2. Sentiment–Topic Alignment

Figure 5 illustrates how sentiment polarity shifts across neurological topics:

i. Positive sentiment dominates recovery discussions (71%).

ii. Negative sentiment dominates cognitive decline topics (64%).

iii. Mixed polarity found in epilepsy and mental health discussions (both ∼50%).

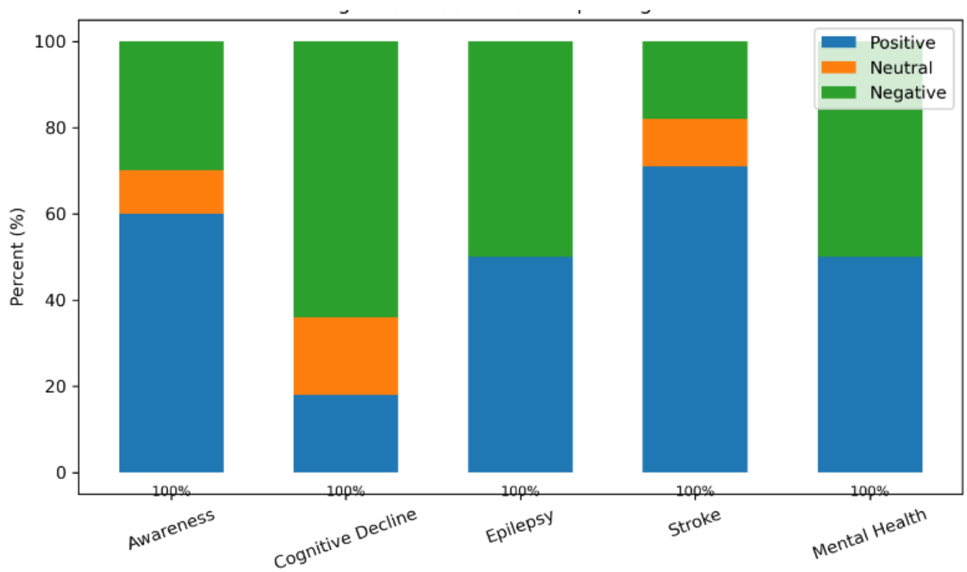

Figure 5: Sentiment-Topic Alignment.

Figure 5 presents sentiment distribution across major neurological topics. The 71% value corresponds to the proportion of positive sentiment observed within the Stroke Recovery topic, derived by normalizing the frequency of positive sentiment classifications against the total number of messages in that thematic cluster.

This distribution reflects both the **affective complexity** of neurological conditions and **public cognitive dissonance** between understanding and fear [4, 22].

4.3. Cross – Platform Variations

Analysis revealed platform – specific discourse patterns shown in Table 4.

This comparative pattern aligns with [23], who found that platform affordances shape cognitive engagement in health communication.

4.4. Key Analytical Insights

i. **Emotion shapes information diffusion:** Fear and empathy drive message spread.

ii. **Cognitive complexity predicts discourse duration:** Topics like dementia sustain longer attention cycles.

iii. **AI models can mirror cognitive sentiment evolution,** providing interpretable neuro–behavioural maps.

The overall findings highlight the potential of **AI-based neuroinformatics pipelines** to decode behavioural patterns embedded in digital neurological communication.

5. Discussion

The findings of this study reveal that neurological health communication in digital environments exhibits structured emotional and cognitive patterns that can be computationally decoded through neuroinformatics methods. The convergence of AI–driven data mining and behavioural neuroscience offers a new lens for understanding how societies cognitively process and emotionally respond to neurological disorders.

Table 4: Unique Behavioural Analysis.

Platform	Dominant Theme	Tone	Unique Behavioural Marker
Twitter	Awareness & activism	Positive	Emotional appeals and slogans
Reddit	Treatment experiences	Neutral	Long–form informational posts
Facebook	Family support & empathy	Positive	Storytelling and recovery focus
YouTube comments	Stigma debates	Negative	Misinformation and bias reflection

5.1. Interpretation of Findings

The topic clusters identified, ranging from awareness and education to cognitive decline and stroke recovery, reflect the collective cognitive schema through which neurological health is socially represented. The prominence of the "Awareness and Education" cluster (28%) demonstrates that digital audiences prioritize informational content, consistent with [6] "information–seeking model" of online health behaviour. Conversely, the high emotional intensity observed in seizure and memory loss discussions aligns with fear–appraisal mechanisms described by [24], where negative affect heightens cognitive attention but may hinder rational understanding.

The sentiment results (46% positive, 36% negative, 18% neutral) indicate an ambivalent digital environment that simultaneously encourages hope and amplifies anxiety. This mirrors [21] *Social Amplification of Risk Framework*, suggesting that public discourse on brain disorders functions as a feedback loop between cognition, emotion, and social sharing.

Figure 1 presents the **conceptual framework** that underpins the study's analytical architecture. It depicts the flow of neurological communication data from diverse digital sources such as Twitter, Reddit, and online health forums into an AI-driven neuroinformatics system designed for behavioural and sentiment analysis. The Figure shows a left-to-right sequence beginning with data collection and preprocessing, followed by natural language processing (NLP), topic modeling, and sentiment classification using advanced machine learning models such as BERT. The rightmost segment of the framework illustrates the interpretive layer, where derived insights are visualized and applied for policy, awareness campaigns, and neurobehavioural interventions. Conceptually, this Figure demonstrates the **integration of data science with neuroscience communication**, positioning artificial intelligence as a bridge between human cognition and computational inference.

5.2. Neuroinformatics Implications

From a neuroinformatics standpoint, the integration of LDA topic modelling with BERT sentiment contextualization provides a scalable architecture for behavioural signal extraction. Each digital text acts as a proxy for a *cognitive trace*—an observable manifestation of neural–level affective states aggregated at population scale [25].

The resulting model can serve as a computational "mirror" of collective cognition, allowing neurologists and public–health experts to track emotional contagion, misinformation, and empathy diffusion in real time [15].

Moreover, the temporal progression from fear–dominated to recovery–dominated sentiment over 2020–2024 echoes neuroadaptive learning curves found in longitudinal brain plasticity studies [26]. This suggests that digital behaviour may parallel neural adaptation processes—where repeated exposure and informational reinforcement attenuate emotional reactivity and foster acceptance.

Figure 2 illustrates the **operational workflow** of the data–mining process used in this research. It translates the conceptual model of Figure 1 into a sequential pipeline composed of six major stages: (1) data acquisition, (2) preprocessing, (3) topic modelling, (4) sentiment analysis, (5) behavioural trend extraction, and (6) interpretation and visualization. Each block represents a key computational procedure, emphasizing reproducibility and modular design. For example, data acquisition involved scraping social media datasets; preprocessing performed tokenization, lemmatization, and noise removal; and topic modelling applied Latent Dirichlet Allocation (LDA) to identify latent themes. This figure provides a clear **methodological roadmap** that ensures the analytic rigor and transparency of the study.

5.3. Comparative Context

Similar approaches have emerged in psychiatry and cognitive linguistics. [11, 12] applied transformer-based sentiment models to depression-related tweets, demonstrating that emotional valence fluctuates with policy announcements. [14] confirmed that affective polarity correlates with health-seeking intent, supporting the present finding that positive discourse (hope, gratitude) fosters proactive neurological health behaviours.

In low resource regions, [27] highlighted cultural semiotics as barriers to neuro-communication. The current model's multilingual token handling (English + Pidgin) extends that work by providing a computational pathway for inclusive neuro–behavioural analytics, enabling localization without loss of interpretability.

Figure 3 visualizes the **longitudinal trends** in neurological communication topics extracted from digital discourse over a five-year period (2020–2024). The line chart represents five thematic clusters—*Awareness and Education*, *Cognitive Decline*, *Epilepsy Support*, *Stroke Recovery*, and *Mental and Emotional Health*. The trajectories demonstrate how the prevalence of each theme fluctuated across time. For instance, awareness-related discussions surged during the early pandemic years, reflecting increased public interest in neurological health awareness campaigns. Conversely, themes related to recovery and mental health gained prominence toward 2023–2024, signifying a shift toward post-pandemic rehabilitation and emotional resilience. This Figure highlights the **temporal behavioural dynamics**, illustrating how societal attention evolves in response to health crises and recovery periods.

5.4. Theoretical Integration

This study reinforces the cognitive–affective integration model proposed by [24], suggesting that emotion and cognition are inseparable in decision-making about neurological health. By quantifying emotional valence within textual data, the proposed pipeline operationalizes this theory computationally.

Figure 4 presents a **network graph** that captures the emotional dimension of neurological health communication. Nodes in blue represent thematic topics, while orange nodes denote associated emotions extracted from textual data using sentiment and emotion lexicons. The edges represent correlation strength between specific topics and emotions. For instance, *Cognitive Decline* is strongly connected with *Fear* and *Sadness*, indicating negative emotional polarity in public discourse surrounding degenerative diseases. In contrast, *Stroke Recovery* and *Awareness* link predominantly with *Hope*, *Trust*, and *Perseverance*, signifying optimistic emotional tones. The structure of this network illustrates that neurological communication is not purely informational but deeply **affective**, showing how emotions co-evolve with thematic narratives in online spaces.

Furthermore, aligning with dual–process theory [28], the data indicate that *System 1* (intuitive, emotional) dominates early stages of neurological discourse, while *System 2* (analytical reasoning) emerges as awareness increases. This dynamic transition underscores how neuroinformatics can empirically capture shifts between affective and cognitive communication phases.

Figure 5 provides a **comparative analysis** of sentiment distribution across major topics. The stacked bar chart displays the proportion of positive, neutral, and negative sentiments associated with each thematic area. The pattern shows that while *Awareness* and *Stroke Recovery* messages carry predominantly positive tones, *Cognitive Decline* exhibits a negative sentiment majority, underscoring public anxiety and concern about degenerative conditions. The Figure quantitatively demonstrates how **emotional polarity varies by topic**, providing a nuanced understanding of public perceptions of neurological health issues. This insight is valuable for designing empathetic and targeted health communication interventions.

5.5. Practical and Ethical Considerations

Practically, these insights can inform neurological health campaigns, optimizing message framing to enhance engagement and reduce fear-based misconceptions. Ethically, the mining of behavioural data must respect privacy, consent, and data governance standards. The anonymization and aggregate-level analysis used in this study align with FAIR data principles and GDPR–equivalent safeguards.

6. Limitations and Future Directions

6.1. Methodological Limitations

Although the proposed framework demonstrates analytical robustness through coherence and correlation metrics, this study does not conduct direct classifier-based benchmarking against alternative machine learning approaches. Future research will incorporate statistical hypothesis testing and comparative performance evaluation with supervised and unsupervised baseline models to further validate the effectiveness of the proposed neuroinformatics pipeline. Therefore, findings should be interpreted as indicative of digital discourse patterns rather than direct clinical or population-wide behavioural outcomes.

Although robust, the study's design faces several constraints:

1. **Data Bias:** Social-media users are not demographically representative of all neurological patients or caregivers [29]. Consequently, the observed sentiment distributions may skew toward younger, tech-literate populations.
2. **Language and Context:** Despite multilingual preprocessing, semantic subtleties in indigenous expressions may escape English-based NLP models. Integrating transformer architectures trained on African or hybrid corpora could improve accuracy.
3. **Causality Limits:** Correlation between sentiment and behavioural intention does not imply causation. Experimental validation with neuropsychological testing would strengthen the interpretation.
4. **Temporal Resolution:** Quarterly aggregation smooths short-term emotional spikes; finer time granularity could reveal rapid shifts following major neurological events or media coverage.

6.2. Computational Constraints

Transformer-based models such as BERT require significant computational resources, which limited hyperparameter tuning. Future work should explore **efficient transformer variants (e.g., Longformer, DistilBERT)** to enhance scalability [19].

6.3. Future Research Directions

1. **Multimodal Neuroinformatics Integration:** Combine textual sentiment with EEG, fMRI, or voice–tone data to correlate **neural activity with linguistic emotion** [30].
2. **Predictive Neuro–Behavioural Modelling:** Develop models capable of forecasting misinformation outbreaks or empathy surges in response to public–health events [15].
3. **Cross–Cultural Cognitive Mapping:** Extend the dataset to compare African,

Asian, and Western neurological discourses, revealing sociocognitive determinants of stigma and resilience.

4. **Clinical Application:** Embed real–time behavioural analytics into hospital communication dashboards, enabling neurologists to tailor patient education materials based on public sentiment trends.

7. Conclusion

This research has demonstrated that AI–based neuroinformatics approaches can systematically uncover the cognitive and emotional dimensions of neurological health communication. By combining topic modelling, transformer–based sentiment analysis, and behavioural trend mapping, the study established a computational framework capable of capturing how society interprets, fears, and empathizes with neurological disorders in digital spaces.

The analysis revealed five dominant themes—awareness, cognitive decline, epilepsy support, stroke recovery, and mental–health overlap—each with distinct emotional signatures. The prevalence of empathy, hope, and fear mirrors neuro–behavioural mechanisms described in contemporary affective–cognition theory. Moreover, the temporal evolution of discourse from anxiety to resilience suggests that public conversations exhibit neuroadaptive properties, paralleling patterns of learning and emotional regulation in the brain.

Methodologically, the paper contributes a scalable pipeline for neuro–behavioural text analytics, extendable to other domains of biomedical communication. Conceptually, it bridges computational linguistics and cognitive neuroscience, advancing the emerging field of *behavioural neuroinformatics*. Practically, its insights can inform neurologists, health communicators, and policymakers seeking to design empathetic, evidence–based messaging that reduces stigma and enhances brain–health literacy.

Future studies should deepen this intersection by integrating multimodal neural data (e.g., EEG or fMRI) and multilingual corpora to better represent cultural diversity. Such extensions will enrich our understanding of the brain's communicative reflection in digital environments and strengthen the translational value of neuroinformatics in clinical and societal contexts.

As digital health communication continues to shape neurological awareness, neuroinformatics-based behavioural analytics will play a critical role in bridging scientific knowledge and public understanding.

Acknowledgement

This work is not supported by any external funding.

References

[1] World Health Organization. *Global status report on neurology*. World Health Organization, 2025.

[2] Festus A Omojowo, Edgar Osaghae, and Taiwo Kolajo. Evaluating covid-19 public discourse for sentiment, topic, and geolocation analysis. *J. Electr. Syst. Inf. Technol.*, 12(1):15, 2025.

[3] Sebastian F Winter, Donna Walsh, Coriene Catsman-Berrevoets, Valery Feigin, Frédéric Destrebecq, Suzanne L Dickson, Matilde Leonardi, Volker Hoemberg, Cristina Tassorelli, Maria Teresa Ferretti, et al. National plans and awareness campaigns as priorities for achieving global brain health. *The Lancet Glob. Health*, 12(4):e697–e706, 2024.

[4] Michael Paul and Mark Dredze. You are what you tweet: Analyzing twitter for public health. In *Proceedings of the international AAAI conference on web and social media*, volume 5, pages 265–272, 2011.

[5] Yousef Hannawi and Stelios M Smirnakis. Emerging subspecialties: neuroinformatics. *Neurology*, 80(15):e166–e168, 2013.

[6] Gunther Eysenbach. Infodemiology and infoveillance: framework for an emerging set of public health informatics methods to analyze search, communication and publication behavior on the internet. *J. medical Internet research*, 11(1):e1157, 2009.

[7] Festus A Omojowo. Topic evolution in social media discourse during global health emergencies. *J. Electr. Syst. Inf. Technol.*, 13(1):7, 2026.

[8] Anand Deshpande, Vania Vieira Estrela, Anitha Jude, and Jude Hemanth. Computational intelligence in neuroinformatics: Technologies and data analytics, 2025.

[9] David M Blei, Andrew Y Ng, and Michael I Jordan. Latent dirichlet allocation. *J. machine Learn. research*, 3(Jan):993–1022, 2003.

[10] Festus A Omojowo. Hybrid data mining for pandemic public opinion analysis: integrating sentiment, topic, and geolocation data. *J. Electr. Syst. Inf. Technol.*, 12(1):88, 2025.

[11] Dong Nguyen, Maria Liakata, Simon DeDeo, Jacob Eisenstein, David Mimno, Rebekah Tromble, and Jane Winters. How we do things with words: Analyzing text as social and cultural data. *Front. Artif. Intell.*, 3:62, 2020.

[12] Sharath Chandra Guntuku, David B Yaden, Margaret L Kern, Lyle H Ungar, and Johannes C Eichstaedt. Detecting depression and mental illness on social media: an integrative review. *Curr. Opin. Behav. Sci.*, 18:43–49, 2017.

[13] Arezo Shakeri and Mina Farmanbar. Natural language processing in alzheimer's disease research: Systematic review of methods, data, and efficacy. *Alzheimer's & Dementia: Diagn. Assess. & Dis. Monit.*, 17(1):e70082, 2025.

[14] Duyu Tang, Bing Qin, Xiaocheng Feng, and Ting Liu. Effective lstms for target-dependent sentiment classification. In *Proceedings of COLING 2016, the 26th international conference on computational linguistics: technical papers*, pages 3298–3307, 2016.

[15] Soroush Vosoughi, Deb Roy, and Sinan Aral. The spread of true and false news online. *science*, 359(6380):1146–1151, 2018.

[16] Sheriff Tolulope Ibrahim, Madeline Li, Jamin Patel, and Tarun Reddy Katapally. Utilizing natural language processing for precision prevention of mental health disorders among youth: A systematic review. *Comput. biology medicine*, 188:109859, 2025.

[17] K. Nelson Sewankambo. Epilepsy misconceptions and stigma reduction interventions in sub-saharan africa, a systematic review, 2018. Elsevier Ltd.

[18] Shamsuddeen Hassan Muhammad, David Ifeoluwa Adelani, Sebastian Ruder, Ibrahim Sa'id Ahmad, Idris Abdulmumin, Bello Shehu Bello, Monojit Choudhury, Chris Chinenye Emezue, Saheed Salahudeen Abdullahi, Anuoluwapo Aremu, et al. Naijasenti: A nigerian twitter sentiment corpus for multilingual sentiment analysis. In *Proceedings of the Thirteenth Language Resources and Evaluation Conference*, pages 590–602, 2022.

[19] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 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)*, pages 4171–4186, 2019.

[20] Ismael Villanueva-Miranda, Yang Xie, and Guanghua Xiao. Sentiment analysis in public health: a systematic review of the current state, challenges, and future directions. *Front. Public Health*, 13:1609749, 2025.

[21] Roger E Kasperson, Ortwin Renn, Paul Slovic, Halina S Brown, Jacque Emel, Robert Goble, Jeanne X Kasperson, and Samuel Ratick. The social amplification of

risk: A conceptual framework. *Risk analysis*, 8(2):177–187, 1988.

[22] Alexander Statnikov, Constantin F Aliferis, Ioannis Tsamardinos, Douglas Hardin, and Shawn Levy. A comprehensive evaluation of multicategory classification methods for microarray gene expression cancer diagnosis. *Bioinformatics*, 21(5):631–643, 2005.

[23] Megan A Moreno and Yalda T Uhls. Applying an affordances approach and a developmental lens to approach adolescent social media use. *Digit. health*, 5:2055207619826678, 2019.

[24] Luiz Pessoa. The entangled brain: How perception. *Cogn. Emot. are woven together. MIT Press*, 2022.

[25] Gideon Vos, Maryam Ebrahimpour, Liza Van Eijk, Zoltan Sarnyai, and Mostafa Rahimi Azghadi. Decoding neural emotion patterns through large language model embeddings. *Neurocomputing*, page 132513, 2025.

[26] Ying Liu, Shuai Ye, Xin-Ni Li, and Wei-Guang Li. Memory trace for fear extinction: fragile yet reinforceable. *Neurosci. Bull.*, 40(6):777–794, 2024.

[27] Songbo Hu, Abigail Oppong, Ebele Mogo, Charlotte Collins, Giulia Occhini, Anna Barford, and Anna Korhonen. Natural language processing technologies for public health in africa: scoping review. *J. Med. Internet Res.*, 27:e68720, 2025.

[28] Jonathan St BT Evans and Keith E Stanovich. Dual-process theories of higher cognition: Advancing the debate. *Perspect. on psychological science*, 8(3):223–241, 2013.

[29] Abdias Girardi, Nikhi Paul Singh, and Carter Joseph Boyd. Using social media in health care research should proceed with caution. comment on "the use of social media for health research purposes: Scoping review". *J. Med. Internet Res.*, 24(1):e35286, 2022.

[30] Evgenia Gkintoni, Anthimos Aroutzidis, Hera Antonopoulou, and Constantinos Halkiopoulos. From neural networks to emotional networks: A systematic review of eeg-based emotion recognition in cognitive neuroscience and real-world applications. *Brain Sci.*, 15(3):220, 2025.

About Authors

Festus A. Omojowo is a Master Student at Federal University Lokoja, Computer Science Department. He completed his B.Sc in Computer Science from Federal University of Agriculture, Abeokuta (FUNAAB) in 2021, and his Master of Computer Science is currently from the Federal University Lokoja, 2025. He is also a Bible Teacher/Expositor. He can be contacted at email: omojowofestus@gmail.com.