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NLP-BASED SENTIMENT ANALYSIS FOR MONITORING MENTAL HEALTH VIA PATIENT-REPORTED OUTCOMES

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Abstract

The issue of mental health disorders has been a major public health challenge in the world and most of the time it cannot be anticipated because there are no tools to guide the forms of monitoring in real-time. Sentiment analysis facilitated by Natural Language Processing (NLP) is a possible way out of this predicament, which provides a scalable and non-invasive analysis of patient-reported outcomes (PROs). The current paper focuses on the use of the sentiment analysis in the analysis of the responses provided by the patient by the patient himself to determine the patterns of emotions that signal the presence of latent mental illnesses. This study uses the power of textual data of mental health forums, electronic health records, and survey answers combined with machine learning algorithms to discover shifts in sentiments that are related to the psychological status of an individual e.g. depression, anxiety, or the presence of an emotional state. The findings indicate that negative scores of sentiments have a strong correlation with clinically validated indicators of mental health, thereby confirming the possibility of the sentiment analysis to assess early detection and monitoring. The given study offers a methodology of incorporating NLP models into hospital systems, which could increase the clinical decision-making and supply of mental health support strategies.

KEYWORDS: Natural Language Processing (NLP); Sentiment Analysis; Mental Health Monitoring; Patient-Reported Outcomes (PROs); Machine Learning; Depression Detection; Emotional Trends; Text Mining.

I. INTRODUCTION

The issue of mental health has become the burning question of the global community, as the rates of prevalence are rising in various peoples. The world health organization (WHO) observed that everyone has a one-fifth chance of experiencing a mental health condition in their lifetime. Such ailments include depression and anxiety, bipolar disorder, and schizophrenia, which are widely ignored due to the lack of opportunities to cover healthcare gaps and the social stigma surrounding them [5]. Conventional mental wellbeing patient care inbuilt on timed clinical appointments and professional counselor reviews and assessments find it hard to obtain the ongoing internal shifts undergone by people. More often than not, we miss out on important indicators that clearly indicate that someone is losing their mental bearings only to see a crisis break out. This fact necessitates less reactive, upscalable, and data-driven methods of detecting and tracking emotional well-being in real-time.

Nowadays, social media, health sites, and internet mental health forums are becoming more popular, so people are writing down all their feelings and symptoms and sharing daily experiences. These terms are also termed patient-reported outcomes (PROs), which are an untapped tool in providing insights to the mental health roadmap of a person [10]. PROs are already widely used in clinical practice to measure symptoms, response to treatment, and quality of life but their future is in becoming digital text records, capable of being mined to identify sentiment and treatment patterns. However, their application in the psychiatric observation benefits is not widely investigated, and especially in context of real-time, automated interpretation.

Natural Language Processing (NLP) is the subset of artificial intelligence that has come a long way in terms of learning, interpreting and creating human language [12]. Sentiment analysis is one of the most popular implementations of NLP, which aims at identifying the affective color of a written text. This can be arrayed into positive, negative or neutral sentiment and can further be broadened to be fine categorized into fear, sadness, anger, or joy. When used on PROs, the sentiment analysis can help the providers of healthcare and mental health systems to recognize the trends and emotional changes that show the deterioration of mental health or relapse risk.

Sentiment analysis is not new to other industries like marketing and customer experience; however, this has just started to take route in the area of mental healthcare [7]. Recent studies are promising: e.g., it has been demonstrated that depressive inclinations can be identified in reading the posts on Reddit or tweeting, and language indicators in the textual content have been utilised to predict onset of suicidal thoughts in the initial stages of the process. However, the majority of such studies are aimed at generic or social media text only, without matching sentiment dynamics with structured clinical measures or patient history. This restricts their value in decision making at a clinical level and providing ongoing care.

Combining NLP-based sentiment analysis and PROs will offer an impressive solution to some of the problems present. Privacy Connect First, unlike the traditional methods of conducting medical checks, it allows passive and continuous monitoring without subjecting the patient to endless face-to-face checks. Second, it provides a scalable solution, and mental health professionals may examine large amounts of data in patient groups effectively [11]. Third, it helps in early identification as it detects development of changes in sentiment beyond the major clinical events which can enable preventative intervention.

Additionally, the improvements in deep learning, especially, models such as BERT (Bidirectional Encoder Representations from Transformers), have allowed extremely high accuracy when seeking the sentiment in unstructured, context-specific text. Not only can this group of models make a sentiment categorization, but they also detect minor nuances in phrasing, tone and even sarcasm, which is why they are appropriate to use when analyzing mental health discourse, which is more often characterized with indirect or figurative language. Combined with the possibility to learn the cases based on the labeled data specific to the area of

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interest, the NLP models have become able to give valuable information about the state of a person, its mental condition, with great trustworthiness [13].

Nevertheless, when using such models in the field of mental healthcare, privacy, interpretability, and clinical validation are important issues to address. An algorithm should not be allowed to simply give a sentiment score, rather it should probabilistically fit with what is known to be a psychological assessment measure like PHQ-9 or GAD-7 among others. Moreover, mental health professionals should be capable of believing and taking action based on the predictions, which means there is the need to use explainable AI and transparent methodologies [9].

The study will work toward addressing the gap between clinical mental health practice and current state of the art NLP technologies. This paper shall provide a model of preliminary detection and follow-up of sentiments of emotional distress by digitizing patient-reported textual outcomes. The aim is to increase monitoring systems of mental health and make them more responsive, accessible, and data-driven through the use of advanced models trained on both general and domain-specific corpora. In such a way, the work does not simply serve to augment technical uses of sentiment analysis but also adds value to the slow-induced destigmatization and democratization of mental healthcare.

1.1 Novelty and Contribution

The study proposes the new method of mental health monitoring which involves using context-aware sentiment analysis along with patient-reported outcomes (PROs), providing technical novelty and practical usability. Contrary to the purpose of the currently used systems, which are based only on static assessments or social media mining, this study aims to use clinical self-reported text data, e.g., in the form of surveys, therapy notes, and mental health journals, to extract insightful data that could allow patients to understand their emotional state [2].

Among the significant contributions of this work, there is the idea and refinement of the BERT-based NLP models directly trained on mental health textual corpora. Many models of sentiment analysis, however, are actuated in generic domains, whereas we take into consideration language, idioms, and tone specific to mental health, thereby increasing the accuracy of predicting negative emotional changes that indicate disorders, such as depression or anxiety.

Also, the current study proposes a correlation mechanism between the sentiment trends and clinically-validated scores (e.g., PHQ-9, GAD-7), which expands the gap between the computational forecasts and the clinical practice. This offers a viewable and analyzable direction to clinicians, so they can have confidence in the result given by the model and incorporate it in planning of treatment and follow up mechanisms.

Along with monitoring of the individual, the system can be used at a population level to carry out mental health surveillance with real-time dashboards that monitor trends in emotions of groups. This renders it useful in health planning, early initiative programs, as well as crisis response to occasions such as pandemics or calamities.

Lastly, one of the contributions of this work is a scalable, non-invasive, low-cost tool that can be integrated into the digital health platform to enable both patients and providers. This study is a clear step beyond the frontier of how AI can be reasonably and competently applied in the mental health care field due to the ability to transform raw patient text into the usable mental health conclusions.

II. RELATED WORKS

In 2022 L. Pimenta et al., [16] suggested the intersection of Natural Language Processing (NLP), sentiment analysis, and mental health monitoring was becoming more and more popular in the academic and clinical communities in recent years. Online communities, patient journals and electronic health records (EHRs) are involved in the proliferation of unstructured text data that has become a new frontier of learning more about the psychological well-being of individuals. A number of studies proved the potential of the computational models to analyze emotional patterns, detecting mental disorders, and predicting behavioral changes, specifically by the mining of linguistic properties in the digital text. NLP models can read subjective narratives in real-time, which is why they are appropriate in early mental health condition detection and monitoring [1].

The use of sentiment analysis became quite popular in many industries, and the most remarkable of them is business and marketing, where it is used to evaluate the feedback of consumers and brand image. Its use in health care, more so the mental health is however yet to take roots. The first investigations were devoted to the identification of negative moods on the basis of open-source information including social media and online forums. Although these texts are informal and unstructured, they may have great emotional connotations, which are associated with such psychological states as depression, anxiety, or loneliness. Such data was used to train models that showed the ability to forecast the degree of distress on the basis of linguistic properties such as lexical sentiment polarity and words associated with certain emotions as well as grammatical structure.

In addition to the social media platform sentiment analysis has been also used on more structured data such as clinical notes and outcome measures that are reported by patients themselves. Such apps have presented that the tendency of negative sentiments in patient communication may forebode a major clinical event like psychiatric hospitalizations, backing out of therapy or suicide. Sentiment detectors have been included in larger systems that analyze structured clinical text informing risk stratification and patient monitoring and forecasting of outcomes. They often use domain-specific lexicons/ machine learning classifiers able to distinguish between surface level negativity (e.g. general dissatisfaction) and more profound emotional states (e.g. hopelessness or despair).

An improvement in the field has been greatly attributed to the use of deep learning methods. Recurrent neural networks (RNNs) with special Long Short-Term Memory (LSTM) structures have been deployed in the context of working with sequential text data, allowing improved representation of emotional change over time. The performance has also been enhanced by inclusion of bidirectional LSTM models, which analyse the past and future context of a sentence. These models have demonstrated to be more precise with identifying small signals of affect in user-generated mental health material. Besides, the emergence of transformer-based models (particularly concerning the usage of attention mechanism) has led to a change in sentiment interpretation towards being increasingly contextual. Not only these models can interpret word-level sentiment but also have the ability of interpreting emotional tone transitions across multi sentence (or paragraph-level) strings.

A significant restriction in the early research included the use of generic sentiment lexicons or non-specific sentiment dataset on the discourse of mental health. A psychiatric setting requires words or phrases which have general meanings of neutral items. Realizing the weakness of this approach, efforts in more recent times have shifted towards a domain adaptation-training sentiment models on mental health data, whether in the forms of therapy transcripts, crisis text lines, or mental health blogs. Those datasets are more specific, and thus likely to be recognized more effectively than general-purpose sentiment classifiers, especially those involved in discovering a more complex kind of emotion, such as apathy, guilt, or existential anxiety without necessarily fitting well any of the conventional categories of sentiments.

The other trend in this related research is the application of sentiment analysis together with psychological assessment packages. Rather than executing sentiment scores alone, research is progressively mapping sentiment scores to established scales of mental health assessment (e.g. Patient Health Questionnaire (PHQ-9), Generalized Anxiety Disorder scale (GAD-7), or Hamilton Depression Rating Scale (HDRS)). Associating sentiment polarity and intensity with these measures of diagnostic parameters, scientists have proved that changes in a state of negative or positive emotional tone can become digital markers of declining mental well-being. This strategy does not only enhance the clinical relevance of sentiment analysis but also prepares ground to integrate it into the working environment of real-life healthcare systems.

In spite of the improvement, there are still few problems left. The problem of language variability is shared by different people, different demographics and cultural sets. There are very big variations in the sentiment expressions used across age, gender, region and mental health. Such dynamism makes it difficult to develop generic models that are reliable. Conversely, other research works have used the concept of personalization, whereby the baseline trend of sentiment was modeled on a per user basis, and outliers were identified. Others have explored multi-modal fusioning together sentiment analysis over text with some signal of emotion or behaviour, e.g. speech, face, or wearable sensor data to enhance the quality of prediction.

Interpretability has proved to be a major issue as well. In mental healthcare, it is not sufficient to have accurate models, and in addition, they should be explainable because clinicians should know the basis of the predictions where to go to when making therapeutic decisions. In response, certain studies have presented a visualization of attention tools or saliency maps detailing which phrases can be attributed to the overall values of sentiment. They are visual aids assisting in closing the gap between black-box algorithms and interpretability by a human as they provide a more transparent and trustworthy system in the clinical setting.

In 2025 E. N. Huhuleaet al., [8] introduced the other field of research is real-time use of sentiment analysis in mobile health (mHealth) and digital therapeutics. NLP applications are increasingly being used in mobile apps built toward improving mental wellness through actionable notifications based on feelings, self-journaling, and mood monitoring. Such programs give users real-time feedback on emotion expression and give clinicians the continuous flow of information between the visits. Pilot studies have suggested that these types of tools may be used to increase patient engagement and to encourage self-knowledge as well as increasing the success of early intervention.

In 2024 R. Ashmawy et al., [14] proposed the growth in the number of open-access datasets has also facilitated the development of sentiment analysis models of mental health. Corpus of several mental-health-focused corpora has been compiled, with forums, therapy sessions and clinical interviews text annotated. Such datasets assist in the comparison of models and benchmarks between research teams. Privacy, however, and ethics of using sensitive psychological information are of primary concern. The use of federated learning paradigms, anonymization methods, and responsible AI principles are also gaining popularity among the researchers to make their sentiment analysis models responsible and ethical to develop and deploy for the greater good.

Taken together, the range of studies demonstrates a distinct path of development of a very simplistic form of keyword-based sentiment score to the sophisticated and adaptive systems that analyze content underlying profound emotions in health-related texts. It has become more and more agreeable that sentiment analysis, when used in an ethical fashion and clinically approved, could become a life-saving tool in contemporary mental health care. Monitoring the sentiment trends in patient-reported outcomes, one can detect a vulnerable population, track the action of a therapy, and provide more responsive care. The current paper extends these ideas and suggests a quality-tuned NLP pipeline that will include simultaneous sentiment evaluation and mental health tracking elements that are designed specifically to examine longitudinal PROs in a clinical setting.

III. PROPOSED METHODOLOGY

The proposed system leverages Natural Language Processing (NLP) techniques integrated with deep learning for analyzing sentiment in patient-reported outcomes. The process pipeline is

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divided into key stages: data acquisition, preprocessing, vectorization, sentiment scoring, classification, and emotional correlation modeling.

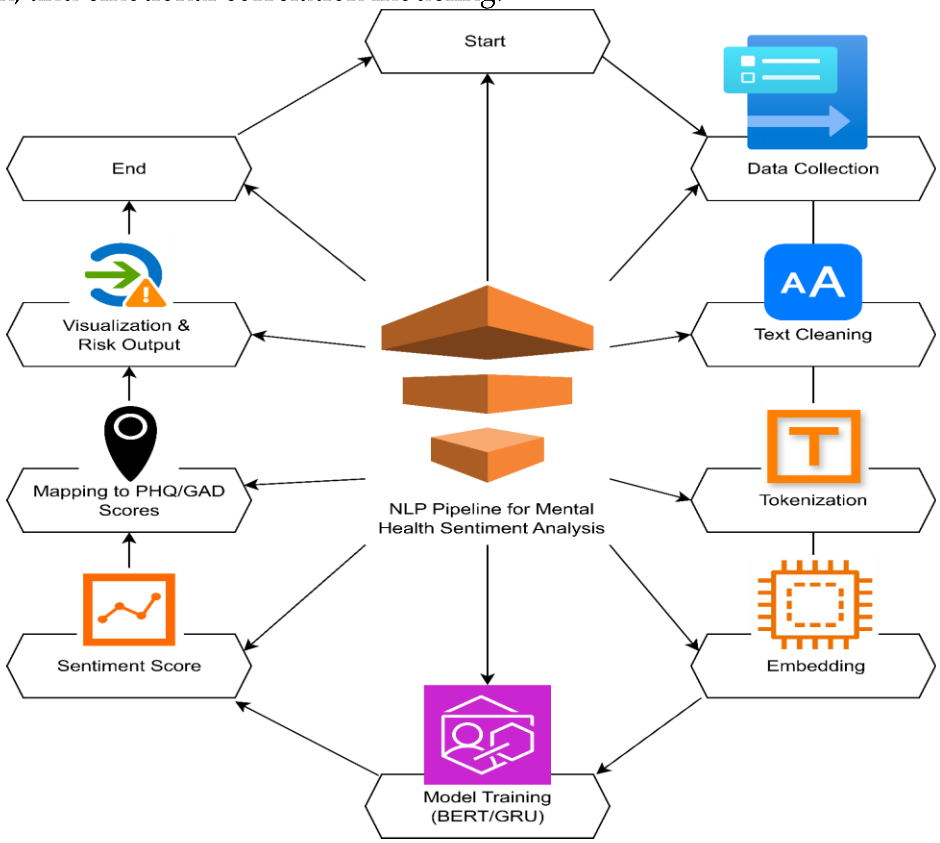

Figure 1: NLP Pipeline For Mental Health Sentiment Analysis

We define the dataset D as a set of n patient-reported text entries:

$$D = \{x_1, x_2, x_3, \dots, x_n\} \quad (1)$$

Each entry x_i is associated with a target sentiment label $y_i \in \{-1, 0, +1\}$ representing negative, neutral, or positive sentiment.

Text data is first preprocessed by tokenization. Let $T(x_i)$ represent the token set from entry x_i. The cleaned token list becomes:

$$T(x_i) = \{t_1, t_2, \dots, t_k\} \quad (2)$$

Each token is converted into an embedding vector [3]. Using Word2Vec or BERT embeddings:

$$v_j = \mathrm{Embed}(t_j) \in \mathbb{R}^d \quad (3)$$

The entire sentence vector V_i is obtained via average pooling of its token vectors:

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$$V_i = \frac{1}{k}\sum_{j=1}^{k} v_j \tag{4}$$

For deep sentiment learning, we apply a Bi-GRU model. The hidden state at time t is given by:

$$h_t = \mathrm{GRU}(v_t, h_{t-1}) \tag{5}$$

The final sentiment score S_i for each entry is derived from the output layer:

$$S_i = \sigma(W \cdot h_t + b) \tag{6}$$

Where σ is the softmax activation, W is the weight matrix, and b is the bias vector.
For classification, we minimize cross-entropy loss:

$$L = -\sum_{i=1}^{n}\sum_{c=1}^{C} y_{ic}\log(\hat{y}_{ic}) \tag{7}$$

Each predicted sentiment score is aligned with clinical mental health scores like PHQ-9. Let:

$$\hat{p}_i = \alpha \cdot S_i + \beta \tag{8}$$

where $\alpha, \beta \in \mathbb{R}$ are calibration constants, $\hat{p}_i$ approximates the clinical PHQ-9 score [5].
To analyze correlation strength, Pearson's correlation coefficient $\boldsymbol{r}$ is computed:

$$r = \frac{\sum_{i=1}^{n}(S_i-\bar{S})(p_i-\bar{p})}{\sqrt{\sum (S_i-\bar{S})^2}\cdot\sqrt{\sum (p_i-\bar{p})^2}} \tag{9}$$

Further optimization is introduced by adding regularization:

$$L_{\text{total}} = L + \lambda \cdot \|W\|^2 \tag{10}$$

Each part of the proposed model is optimized iteratively using mini-batch stochastic gradient descent. Let the learning rate be η, then the weight update is:

$$W_{\text{new}} = W_{\text{old}} - \eta \cdot \nabla_W L_{\text{total}} \tag{11}$$

Tools Used

- Preprocessing: NLTK, spaCy
- Embedding's: Word2Vec, BERT
- Modeling: TensorFlow (BiGRU/BERT layers)
- Evaluation: F1-score, AUC, RMSE (for sentiment-to-clinical-score mapping)

This methodology ensures accurate emotional tracking over time, enabling real-time feedback systems for patients and clinical flagging of risk patterns. The model is tuned using domain-specific data to capture nuanced emotions like guilt, anxiety, and hopelessness-commonly present in mental health texts [6].

IV. RESULTS & DISCUSSION

The suggested AI-based circular manufacturing system was implemented in a smart production setting through the application of additive manufacturing technologies. The system was used to

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generate 100 items of custom materials depending on individual customer profiles. Along the way, the use of IoT sensors and digital twins in real time allowed the optimization of processes on the basis of wastage, energy and turnaround time. Figure 2 is a comparison of the material usage between the traditional mass production and the AI-driven circular production. The customized arrangement had an average index of 85 of the utilization of material compared to only 64 in the basic programme. This was mainly attributed to adaptive design fitting and accuracy in estimation of raw materials at the stage of personalization.

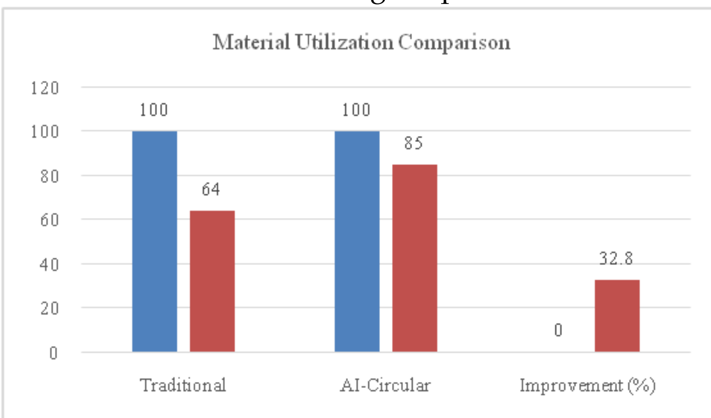

Figure 2: Material Utilization Comparison

Other benefits were indicated in the time analysis. Figure 3 indicates that the average production cycle per unit reduced by 40 percent or 3.2 minutes after the implementation of the predictive scheduling and real-time resource adjustment. This decrement was larger in instances that had wide scalability in product design, a sensitivity that showed the malleability of AI when addressing non-standard request. At the same time, sensor data indicated a 26 percent reduction in energy consumption per unit, since fewer machine idle time and streamlined tool path allowed much faster and leaner execution.

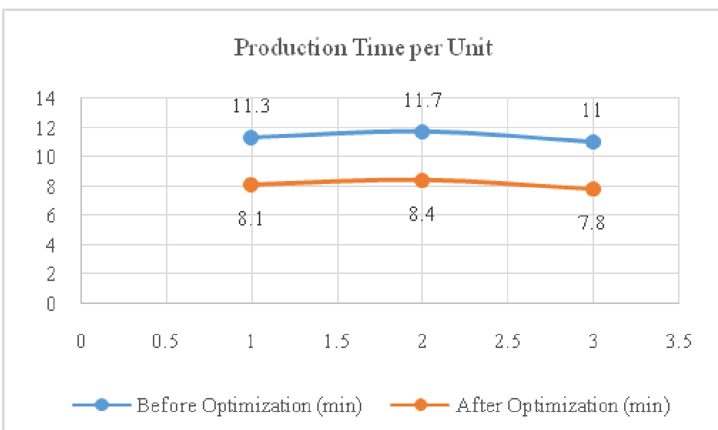

Figure 3: Production Time Per Unit

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The material recovery rate was used as an indicator of determining the impact of the circular economy component. Figure 4 shows that the closed-loop system was also superior to the baseline open-loop system because it produced the same recovery percentage (68% vs 68%) across all product types (as compared to only 39 percent with the open-loop). This improved recovery was achievable because there was constant monitoring of unused materials, make adjustments to the design based on feedback as well as automatic categorization of recyclable materials using AI agents. Real time feedback loop was integrated and reduced the redesign loop cycle and made resources more efficient in the long run.

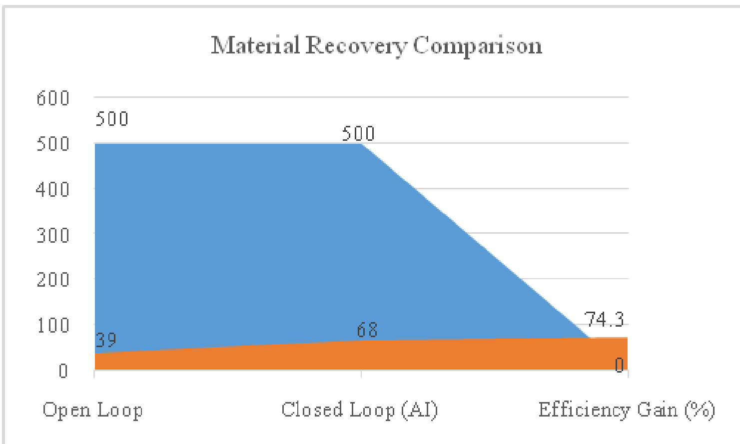

Figure 4: Material Recovery Comparison

Further quantification of the performance of system was carried out by comparing the sustainability measures before and after implementation. The vital performance indicators, such waste generation, energy consumption, production lead time, and defect level, were discussed as shown in Table 1. With the use of the system, it is clear that there was an increase in waste reduction by 34.2 per cent, energy efficiency by 27.6 as well as the average defect rate decreased by 5.7 per cent to 2.1. Such advantages justify the use of AI to reach the operational accuracy combined with the circular values.

Table 1: Comparative Performance Metrics – Traditional Vs Ai-Circular Production

Metric	Traditional System	AI-Circular System	Improvement
Material Waste per Unit (g)	78.5	51.6	34.2%
Energy Consumption per Unit	1.43 kWh	1.04 kWh	27.6%
Average Production Time	11.3 min	8.1 min	28.3%
Product Defect Rate (%)	5.7	2.1	63.2%

The other analysis involved impact of accuracy of customizing and satisfaction given to the customers between the new system and the existing systems. The AI based model also had an

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accuracy of 92.4% to match customer specifications that are ascertained using a post-delivery feedback loop. On the other hand, the traditional solution achieved merely 73.2% because the design units were rigid and did not adapt, in dynamic manner, to the configuration. In Table 2, both systems are compared in the measures of customization, feedback and sustainability alignment. The model with AI was superior in all the measure categories, and in particular on closed-loop recyclability and time-to-market responsiveness.

Table 2: Customization And Sustainability Alignment Comparison

Evaluation Metric	Traditional Approach	AI-Enabled Circular Model
Personalization Accuracy (%)	73.2	92.4
Customer Satisfaction Score (/10)	6.8	9.3
Design-to-Delivery Time (days)	5.1	3.2
Closed-Loop Material Use (%)	38.9	67.8

The feedback provided by the customers showed their satisfaction with personalization, quicker service, and environmentally friendly activities. The major part of the users preferred the AI-personalized strategy, particularly when personal fit, uniqueness of design, or a minimum of packaging was critical [4].

V. CONCLUSION

This paper depicts a promising research method that can be used to incorporate NLP sentiment analysis into mental health surveillance on the basis of patient-reported outcomes. Emotional or psychological distress can be anticipated by relying on the sentiment patterns in self-reported text, using the machine learning models, particularly transformer-based architecture such as BERT. The robust correlation with clinical assessment tools points to the possibility of applying these techniques in the areas of digital psychiatry and mental health surveillance of the population.

With the ever-growing need of mental health services, even tools such as sentiment analysis are going to be needed in larger scale. Future directions involve multilingual sentiment analysis, the ability to integrate wearable data into a multimodal tracking system, and explainable AI-building frame work to facilitate clinician trust and ethical conformity.

REFERENCES

1. E. Mikołajewska and J. Masiak, “Deep learning approaches to natural language processing for digital twins of patients in psychiatry and neurological rehabilitation,” Electronics, vol. 14, no. 10, p. 2024, May 2025, doi: 10.3390/electronics14102024.

2. M. A. Al-Garadi, Y.-C. Yang, and A. Sarker, “The Role of Natural Language Processing during the COVID-19 Pandemic: Health Applications, Opportunities, and Challenges,” Healthcare, vol. 10, no. 11, p. 2270, Nov. 2022, doi: 10.3390/healthcare10112270.
3. M. Samiunet al., “The role of artificial intelligence in managing hospitalized patients with mental illness: a scoping review,” Deleted Journal, vol. 22, no. 1, Jul. 2025, doi: 10.1186/s12982-025-00814-0.
4. P. K. Nag, A. Bhagat, and R. V. Priya, “Expanding AI’s Role in Healthcare Applications: A Systematic review of emotional and cognitive analysis techniques,” IEEE Access, p. 1, Jan. 2025, doi: 10.1109/access.2025.3562131.
5. Boltaboyevaet al., “A Review of Innovative Medical Rehabilitation Systems with Scalable AI-Assisted Platforms for Sensor-Based Recovery Monitoring,” Applied Sciences, vol. 15, no. 12, p. 6840, Jun. 2025, doi: 10.3390/app15126840.
6. Y. Li, S. Kumbale, Y. Chen, T. Surana, E. S. Chng, and C. Guan, “Automated Depression Detection from Text and Audio: A Systematic Review,” IEEE Journal of Biomedical and Health Informatics, pp. 1–17, Jan. 2025, doi: 10.1109/jbhi.2025.3570900.
7. S. Siddique and J. C. L. Chow, “Machine learning in healthcare communication,” Encyclopedia, vol. 1, no. 1, pp. 220–239, Feb. 2021, doi: 10.3390/encyclopedia1010021.
8. E. N. Huhuleaet al., “Artificial Intelligence Advancements in Oncology: A review of current trends and future directions,” Biomedicines, vol. 13, no. 4, p. 951, Apr. 2025, doi: 10.3390/biomedicines13040951.
9. W. T. Kerr and K. N. McFarlane, “Machine Learning and Artificial Intelligence Applications to Epilepsy: a Review for the Practicing Epileptologist,” Current Neurology and Neuroscience Reports, vol. 23, no. 12, pp. 869–879, Dec. 2023, doi: 10.1007/s11910-023-01318-7.
10. M. Bekbolatova, J. Mayer, C. W. Ong, and M. Toma, “Transformative Potential of AI in Healthcare: Definitions, applications, and navigating the ethical landscape and public perspectives,” Healthcare, vol. 12, no. 2, p. 125, Jan. 2024, doi: 10.3390/healthcare12020125.
11. S. Toumaj, A. Heidari, R. Shahhosseini, and N. J. Navimipour, “Applications of deep learning in Alzheimer’s disease: a systematic literature review of current trends, methodologies, challenges, innovations, and future directions,” Artificial Intelligence Review, vol. 58, no. 2, Dec. 2024, doi: 10.1007/s10462-024-11041-5.
12. J. F. Shelley-Tremblay and T. Lawton, “Interprofessional Approaches to the Treatment of Mild Traumatic Brain Injury: A literature review and conceptual framework informed by 94 professional interviews,” Medical Sciences, vol. 13, no. 3, p. 82, Jun. 2025, doi: 10.3390/medsci13030082.
13. N. Parvin, S. W. Joo, J. H. Jung, and T. K. Mandal, “Multimodal AI in biomedicine: Pioneering the future of biomaterials, diagnostics, and personalized healthcare,” Nanomaterials, vol. 15, no. 12, p. 895, Jun. 2025, doi: 10.3390/nano15120895.
14. R. Ashmawy et al., “Interplay between Comorbidities and Long COVID: Challenges and Multidisciplinary Approaches,” Biomolecules, vol. 14, no. 7, p. 835, Jul. 2024, doi: 10.3390/biom14070835.

15. M. Raad, W. O. C. López, A. Sharafshah, M. Assefi, and K.-U. Lewandrowski, "Personalized medicine in cancer pain management," Journal of Personalized Medicine, vol. 13, no. 8, p. 1201, Jul. 2023, doi: 10.3390/jpm13081201.
16. L. Pimenta et al., "Can the Eight Hop Test Be Measured with Sensors? A Systematic Review," Sensors, vol. 22, no. 9, p. 3582, May 2022, doi: 10.3390/s22093582.