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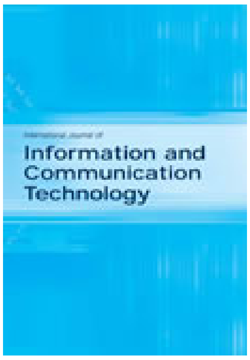

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Junmei Bai

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Temporal convolutional networks with language models for decoding music preferences in mental health profiling

Junmei Bai

College of Preschool Education,
Henan Information and Statistics Vocational College,
Zhengzhou 450018, China
Email: Hntybjm@126.com

Abstract: Music preferences serve as crucial behavioural clues for decoding mental health states. Music provides a continuous and emotionally rich behavioural signal that is less influenced by social desirability biases compared to self-reported data, making it a robust indicator for mental health assessment. However, traditional analysis methods struggle to simultaneously account for the temporal dynamics of music listening and its rich semantic information, resulting in limited decoding efficacy. Previous studies attempted hybrid models but often faced overfitting or computational inefficiency, which motivated our design of a more integrated framework. To address this, we propose an innovative framework that integrates temporal convolutional networks with pre-trained language models to capture both the sequential patterns of music consumption and the emotional semantics of lyrics content. Our validation on a public dataset containing over 100,000 records demonstrates that this model achieves approximately 8.5% higher accuracy than single-modal benchmark methods in mental health state assessment tasks. It also effectively identifies specific musical features associated with depressive and anxious tendencies. This work provides a novel technical pathway for achieving non-invasive, dynamic mental health screening.

Keywords: temporal convolutional networks; language models; music preferences; mental health; multimodal fusion.

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Biographical notes: Junmei Bai is an Associate Professor in the College of Preschool Education at Henan Information and Statistics Vocational College, China. She received a Bachelor's degree from Henan University and a Master's degree from Zhengzhou University. Her research interests are preschool education, music education, higher vocational education, psychology, and machine learning.

1 Introduction

As a language, which has no boundaries of cultures and countries, music has always been considered to be a means of personal feelings (Öz, 2023). The availability of increased user listening behaviour data due to the spread of digital music platforms over recent years presents the computational perspective of problems of user musical tastes with mental health with unprecedented opportunities to decipher this complex relationship. Studies have shown that the music preference of anyone is not by chance but instead indirect yet real representation of the way an individual feels, his personal character and even the level of his psychological stability. As an example, depressive individuals might be more attracted to slower and darker sounding music, and anxiety might be associated with the need to listen to particular genres, say the highly stimulating or, on the contrary, very smooth types of compositions (Amgoth and Jana, 2014). Such a correlation makes music preference analysis a promising, emerging research area of where non-invasive dynamic mental health assessment can be conducted, which has great practical importance in resolving the mushrooming mental health issues in the world (Pompeo et al., 2024).

At present, studies in the area are mostly driven towards two technical directions (Asa and Daniel, 2015). The former deals with audio signal processing-based methods that are used to extract low-level acoustic music features, including pitch, rhythm, and spectral characteristics. They are further used to build predictive models based on standard machine learning methods (e.g., support vector machines, random forests) or simpler deep learning models (e.g., convolutional neural networks). Such studies have proven to statistically correlate content of music with mental health indicators. The other method uses natural language processing to interpret information of music nature, including lyrics (Han, 2024). Neural snapshots such as bidirectional encoder representations of transformer (BERT) and enhanced BERT pretraining strategy could appear to capture detailed emotional semantics and narrative themes in a song and provide a new layer of understanding of the psychological effect that music has on listeners. Nonetheless, both mainstream approaches are limited in some way. The temporal dynamic of the circumstance of music as an art is usually lost by pure audio analysis tools. It is not the influence of a piece of music that is defined at one moment, but a synergistic development in the melody, harmony and rhythm in the time dimension (Wilbourne, 2025). On the other hand, semantic content can be fully abstracted in pure lyric analysis approaches, and cannot analyse instrumental pieces that do not contain lyrics, and lapse away from the musical sound-temporal context of music (Fernández, 2024).

Importantly, listening to music in actual situation is the paradigmatic and multimodal and temporal activity (Mudau and Sikhosana, 2024). Streaming listening patterns are enormous longitudinal information, including profound psychological hints like tendencies toward mood changes, the degree of musical discoveries and consistency of preferences (Yoshizawa et al., 2023). As an example, listening to many sad songs with very similar emotional sounds one right after another, rather than alternating between the cheerful songs and the sad ones, is probably a sign of drastically different mental conditions. This is because the current studies have serious limitations when it comes to effectively combining this heterogeneous information, that is, the temporal listening patterns of music and the audio/semantic content of music (Lilley, 2024). The classic version of recurrent neural networks (RNNs) and its derivatives, long short-term memory (LSTM), and gated recurrent (GR) units, have the drawbacks of a gradient vanishing (or gradient explosion) issues with long sequences and can not be easily parallelised to train, leading to poor efficiency. In spite of the fact that, compared to RNNs, TCNs show better performance in the modelling of long sequences, i.e., using such structures as causal convolutions and residual connections, the success in doing various tasks related to the temporal domain, TCNs find little application in the interdisciplinary field of music-based mental health decoding. Particularly, synergistic integration with deep language models warrants further exploration (Mallada et al., 2014).

Therefore, the core motivation of this research lies in addressing the aforementioned research gap and tackling the challenge of how to deeply integrate music's temporal behavioural patterns with its deep semantic content to decode mental health more accurately. We recognise that a computational framework capable of fully understanding 'when, in what sequence, and what content (including its sound and meaning) a user listens to' is crucial for advancing this field. Based on this, this research aims to explore and implement a novel fusion mechanism between TCNs and advanced language models. The goal is to construct an intelligent system capable of end-to-end, collaborative learning of effective representations from complex multimodal music data, ultimately enabling refined and interpretable decoding of an individual's mental health state (Aditya, 2025).

2 Related research work

2.1 Music preferences as behavioural markers of mental health

Music listening, as a daily and highly personalised activity, has been shown through multiple studies to exhibit systematic correlations between preference patterns and an individual's mental health status (Kochar et al., 2024). From a psychological perspective, the theory of music-based emotion regulation posits that individuals often consciously select music to manage their emotions – for instance, using uplifting music to boost mood or sorrowful music to seek resonance and catharsis (Edler and Valentino, 2024). These selection preferences indirectly reflect their current psychological state and needs. In computational psychiatry, researchers are leveraging this connection to develop mental health assessment models through quantitative analysis of music consumption data. Initial research mainly used features designed by hand, including audio properties such as Mel-frequency cepstral coefficients, beat strength, and tonality, with a classifier, such as support vector machine or random forest to estimate signs of depression or anxiety. Nevertheless, such methods tended to consider a single song or listening process a static, isolated sample, forgetting that the music listening is a dynamic process, time changing endeavour. The sequence of songs that the users will listen to at various times of time are automatically rich information. As an illustration, the reduction in the variety of listening or an extended low emotional tone can be a better indicator of mental health problems than the aspect of a particular song. Hence, the enhancement of the decoding accuracy is optimal with the treatment of music preferences as a time-based behavioural characteristic and the creation of models that can effectively describe their long-term relationships.

2.2 The principles and advantages of TCN

To model long-term dependencies in music listening sequences, we introduce TCNs. TCNs are a class of convolutional architectures specifically designed for sequence modelling (Ding et al., 2024). Their core lies in ensuring efficient processing of temporal data through causal convolutions and dilated convolutions. Unlike traditional convolutional neural networks, the output at time step *t* in a TCN depends only on the data from time step *t* and earlier in the input sequence. This strictly adheres to temporal causality, preventing leakage of future information. This property is achieved through causal convolutions, whose mathematical form can be expressed as:

$$y[t]=\sum_{k=1}^{K} x[t-(K-k)]\cdot w[k]+b \tag{1}$$

where, x is the input sequence, $y[t]$ is the output at time t, w is the convolutional kernel weight of length K, and b is the bias term.

To expand the receptive field without significantly increasing parameters and computational complexity, TCN employs dilated convolutions. For a convolutional layer with dilation factor d, the operation is defined as:

$$y[t]=\sum_{k=1}^{K} x[t-d\cdot(K-k)]\cdot w[k]+b \tag{2}$$

By stacking multiple layers of dilated convolutions and allowing the dilation factor d to grow exponentially with network depth (e.g., $d = 2^l$ where l is the layer index), TCNs can efficiently capture dependencies over extremely long ranges in sequences.

Additionally, TCNs typically draw inspiration from residual network by incorporating residual connections to mitigate the vanishing gradient problem in deep networks, ensuring stable training. A basic residual block can be represented as:

$$\mathbf{o}=\text{Activation}(\mathbf{x}+\mathcal{F}(\mathbf{x})) \tag{3}$$

where, $\mathbf{x}$ is the block input, $\mathcal{F}$ is the transformation function composed of a series of causal dilated convolutions and nonlinear activation functions, and $\mathbf{o}$ is the block output. Compared to RNNs and their variants (such as LSTMs), TCNs possess inherent advantages including clear structure, stable training (avoiding gradient explosion/vanishing), high parallel computing efficiency, and flexible handling of variable-length inputs. These characteristics make them an ideal choice for processing long-sequence music listening histories. Compared to recurrent architectures like LSTMs, TCNs exhibit superior computational efficiency due to their parallelisable convolutional operations and fixed-depth receptive field. This design significantly reduces training time and memory footprint when processing extensive music listening histories, without compromising the model's ability to capture long-range dependencies. Therefore, TCNs offer a more scalable solution for real-world applications involving lengthy sequential data.

2.3 Applications of language models in music semantic understanding

Music encompasses more than just audio signals; its accompanying textual information – such as lyrics, song titles, and user tags – carries rich semantic content that is crucial for understanding the emotions and themes within music (Kraus and Chandrasekaran, 2010). In recent years, pre-trained language models based on the Transformer architecture, such as BERT, We selected BERT over alternatives like RoBERTa primarily for its well-established bidirectional context encoding and extensive pre-training on diverse corpora, which aligns with the nuanced and often figurative nature of song lyrics. BERT's ability to model deep contextual relationships allows it to effectively interpret subtle emotional cues and thematic shifts within lyrical text. Furthermore, its robust open-source implementation and proven performance on various semantic tasks provided a reliable foundation for our multimodal framework. have achieved revolutionary progress in natural language understanding tasks. By pre-training on large-scale corpora, these models can generate deep context-aware word embeddings. In the field of music analysis, researchers utilise such models to encode lyrics, capturing the emotional semantics and narrative themes of songs. Given a sequence of lyrics $S = s_1, s_2, \ldots, s_N$ the BERT model transforms it into a sequence of context-rich embedding vectors $\mathbf{E} = \mathbf{e}_1, \mathbf{e}_2, \ldots, \mathbf{e}N$. Typically, the model uses the embedding corresponding to the special classification (CLS) token, $\mathbf{e}_{[\mathrm{CLS}]}$, as the aggregated representation of the entire sequence:

$$\mathbf{e}_{[\mathrm{CLS}]} = \mathrm{BERT}(S) \tag{4}$$

This indicates that $\mathbf{e}_{[\mathrm{CLS}]}$ can be regarded as a semantic summary of the entire lyrics, which can then be utilised for downstream CLS or regression tasks. In this manner, language models provide music with a content-based semantic perspective that transcends acoustic features, enabling the model to comprehend concepts closely related to mental health –such as 'heartbreak,' 'joy,' or 'loneliness' – as expressed within the lyrics.

2.4 Existing strategies and challenges in multimodal fusion

Given the multimodal nature of music data (temporal listening behaviour and textual semantics), effectively integrating these heterogeneous information streams presents a core challenge. Existing multimodal fusion methods can be broadly categorised into early fusion and late fusion approaches (Drougkas et al., 2024). Early fusion integrates at the feature level, such as concatenating temporal features extracted by TCN with semantic features extracted by language models before feeding them into a classifier: $\mathbf{z} = [\mathbf{h}\mathrm{TCN}; \mathbf{h}\mathrm{LM}]$. While simple, this approach may overlook interactions between different modal features. Late fusion, conversely, allows each modality to make independent predictions, subsequently merging results through weighted averaging or voting. However, this approach fails to leverage complementary information between modalities during the model training process (Kwak et al., 2025).

More advanced fusion strategies rely on attention mechanisms, which dynamically evaluate the importance of different modal features across varying contexts (Kalamkar and Amalanathan, 2025). At the core of attention mechanisms lies the computation of a weighted context vector through the interaction between a query vector (Query) vector and a set of key-value pairs (Chen et al., 2024). This computational process can be summarised as follows:

$$\alpha_i = \frac{\exp\left(\text{score}\left(\mathbf{q}, \mathbf{k}_i\right)\right)}{\sum_j \exp\left(\text{score}\left(\mathbf{q}, \mathbf{k}_i\right)\right)} \tag{5}$$

$$\mathbf{c} = \sum_i \alpha_i \mathbf{v}_i \tag{6}$$

where, α_i represents the attention weight, and **c** denotes the output context vector. In cross-modal fusion, features from one modality can serve as a query to retrieve relevant information from another modality (functioning as key and value), thereby achieving selective, focused integration. In designing the cross-modal attention module, we prioritised parameter efficiency to ensure the model's practicality for potential deployment. The attention mechanism operates on projected feature vectors without introducing large intermediate layers, keeping the additional parameter count minimal. This lightweight design ensures that the fusion module enhances performance without imposing a substantial computational burden, maintaining the overall model's suitability for integration into resource-conscious applications. However, in the specific task of music preference decoding, designing an efficient attention interaction mechanism that enables deep, bidirectional information complementarity between temporal behavioural patterns and lyrical semantics – and jointly serves the precise inference of mental health states – remains an area not yet fully explored in current research.

3 Technical approach and model architecture

3.1 Problem definition

This study aims to decode users' mental health states through their music listening sequences and corresponding semantic information (Fischer and Mcadams, 2025). We formalise this task as a multimodal sequence classification problem. Specifically, an input instance to the model is defined as:

$$U_i = \left(S_i, L_i\right) \tag{7}$$

where, $S_i = s_1, s_2, \ldots, s_T$ listening sequence of length T for user i, where each element s_t in the sequence is a song identifier(ID). For each song s_t in the sequence, we have its corresponding lyric text data l_t. Thus, the set of lyrics corresponding to the entire sequence is $L_i = l_1, l_2, \ldots, l_T$. The model outputs a mental health state classification label $y_i \in 1, 2, \ldots, C$, where C denotes the total number of categories (e.g., $C = 3$ may correspond to 'healthy,' 'mild symptoms,' and 'severe symptoms').

Our objective is to learn a mapping function f: $(S_i, L_i) \rightarrow$ that collaboratively learns an effective joint representation from sequential listening patterns and lyric semantics, thereby enabling accurate prediction of mental health states y_i.

3.2 Overall model architecture

To address these challenges, we propose a multimodal fusion framework based on TCNs and language models (Pham et al., 2023), whose core architecture is illustrated in Figure 1. The model primarily consists of three core modules:

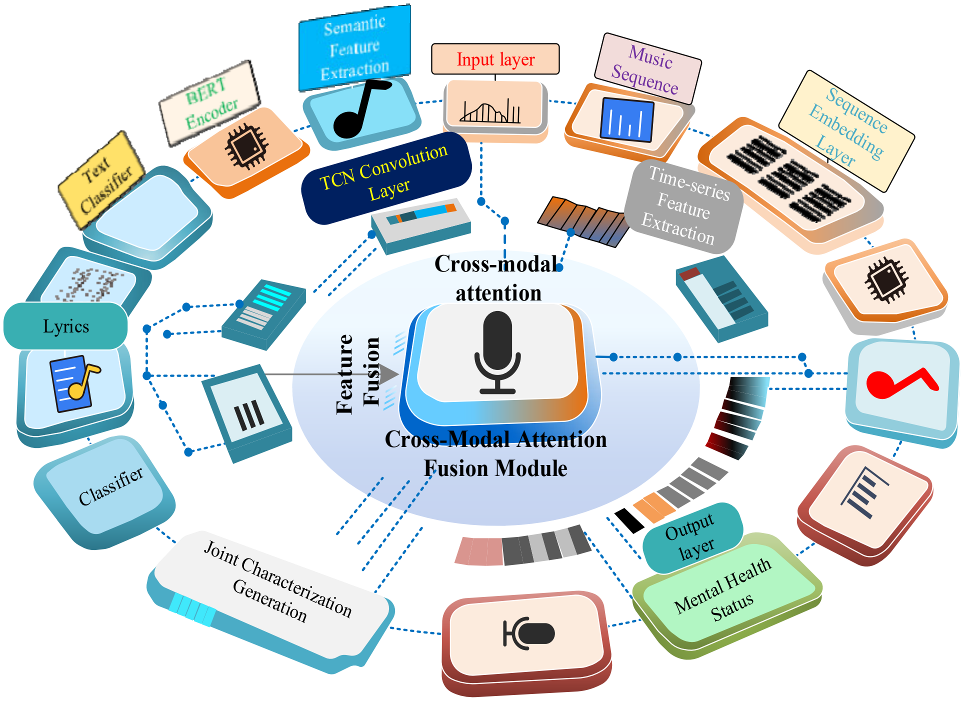
1 the TCN temporal feature extraction module, responsible for extracting temporal features with long-term dependencies from music listening sequences S_i

2 The language model semantic encoding module, which extracts deep semantic features from the lyric set L_i

3 The cross-modal attention fusion module, which dynamically integrates temporal and semantic features to generate the final classification results.

The entire model is trained in an end-to-end manner.

Figure 1 Temporal convolutional network-language model (TCN-LM) fusion model architecture diagram (see online version for colours)



3.3 TCN temporal feature extraction module

Given an input sequence S_i, we first map each song ID s_t to a dense vector representation through an embedding layer:

$$\mathbf{x}_t \in \mathbb{R}^{d_e} \tag{8}$$

where d_e is the embedding dimension. This transforms the discrete ID sequence into a continuous vector sequence:

$$\mathbf{X} = \mathbf{x}_1, \mathbf{x}_2, ..., \mathbf{x}_T \in \mathbb{R}^{T \times d_e} \tag{9}$$

Subsequently, the sequence is fed into a multi-layer TCN architecture for processing. As described in relevant studies, TCNs ensure temporal dependencies through causal dilated convolutions. For layer l, the dilation factor is $d = 2^{l-1}$. The output feature $\mathbf{h}_t^l$ at time step t is computed using the following formula:

$$\mathbf{h}t^l = \text{ReLU}\left(\sum k = 1^K \mathbf{W}_k^l \cdot \mathbf{h}t - d \cdot (K - k)^{l-1} + \mathbf{b}^l\right) \tag{10}$$

where, $\mathbf{h}^{l-1}$ denotes the input sequence from the previous layer (for the first layer, $\mathbf{h}^0 = \mathbf{X}$), K represents the convolution kernel size, and $\mathbf{W}_k^l$ and $\mathbf{b}^l$ are the weight matrix and bias vector at position k in layer l, respectively. Rectified linear unit (ReLU) is used as the activation function.

To stabilise training for deep networks, we introduce a residual connection after every two TCN layers. The computation process for a residual block is as follows:

$$\mathbf{o}^l = \text{Activation}\left(\mathbf{h}^{l-1} + \mathcal{F}\left(\mathbf{h}^{l-1}\right)\right) \tag{11}$$

where, $\mathcal{F}$ represents the transformation function composed of two layers of causal inflation convolutions and their activation functions, with $\mathbf{o}^l$ being the output of this residual block. After stacking L layers of TCN, we obtain a high-level temporal feature representation that captures the long-term dependencies across the entire sequence:

$$\mathbf{o}^l = \text{Activation}\left(\mathbf{h}^{l-1} + \mathbf{H}_{\text{TCN}} = \mathbf{h}_1^L, \mathbf{h}_2^L, ..., \mathbf{h}_T^L \in \mathbb{R}^{T \times d_h}\left(\mathbf{h}^{l-1}\right)\right) \tag{12}$$

where d_h denotes the dimension of the TCN output features. To obtain a sequence-level global temporal representation, we perform average pooling on the features across all time steps. We evaluated several aggregation strategies, including max pooling and attention-based pooling, during preliminary experiments. Average pooling was ultimately selected because it consistently produced the most stable and generalisable representations by incorporating information from all time steps or song features. This approach mitigates the risk of overfitting to single, potentially noisy elements, which is crucial for modelling behavioural sequences where the overall pattern is more informative than outliers.

$$\bar{\mathbf{h}}\text{TCN} = \frac{1}{T} \sum t = 1^T \mathbf{h}_t^L \tag{13}$$

The vector $\bar{\mathbf{h}}\text{TCN} \in \mathbb{R}^{d_h}$ will serve as the representative of the temporal modality and be fed into the subsequent fusion module.

3.4 Semantic encoding module for language models

For each song lyric l_t in the lyric collection L_i, we employ a pre-trained BERT model to extract its semantic representation. First, the lyric text l_t is tokenised and augmented with special tokens before being fed into the BERT model:

$$\mathbf{e}_{[\mathrm{CLS}]}^{t}, \mathbf{e}_{1}^{t}, \ldots, \mathbf{e}_{N}^{t} = \mathrm{BERT}\left(l_{t}\right) \tag{14}$$

Among these, $\mathbf{e}[\mathrm{CLS}]^{t} \in \mathbb{R}^{d_b}$ is the embedding of the CLS token at the beginning of the sequence, which is widely used as the aggregated representation of the entire input sequence, where d_b denotes the output dimension of the BERT model. Thus, for a song sequence of length T, we obtain T song-level semantic vectors:

$$\mathbf{E} = \mathbf{e}[\mathrm{CLS}]^{1}, \mathbf{e}[\mathrm{CLS}]^{2}, \ldots, \mathbf{e}[\mathrm{CLS}]^{T} \in \mathbb{R}^{T \times d_b} \tag{15}$$

To capture the global semantics of the entire lyric sequence, we similarly employ an average pooling operation to aggregate **E** into a global semantic vector:

$$\bar{\mathbf{h}}\mathrm{LM} = \frac{1}{T} \sum t = 1^{T} \mathbf{e}_{[\mathrm{CLS}]}^{t} \tag{16}$$

The vector $\bar{\mathbf{h}}\mathrm{LM} \in \mathbb{R}^{d_h}$ will serve as the semantic modality representative and participate in fusion.

3.5 Cross-modal attention fusion and classification

Simple feature concatenation or late-stage fusion struggles to capture complex interactions between modalities. Therefore, we designed a cross-modal attention fusion module (Yan et al., 2025). This module uses the temporal global feature $\bar{\mathbf{h}}_{\mathrm{TCN}}$ as the query. Our design decision to use the global temporal feature as the query is grounded in the behavioural causality inherent in the task: a user's listening sequence forms the contextual backdrop against which the semantic content of individual songs is interpreted. This setup allows the model to ask, 'Given this pattern of listening behaviour, which lyrical themes are most salient?' Preliminary experiments using the semantic feature as the query yielded marginally inferior results, supporting our hypothesis that the temporal context should guide the semantic selection. with all lyric semantic vectors **E** serving as both key and value. It dynamically calculates the importance of each song's lyric semantics within the broader listening sequence context.

first, we project query, key, and value onto the same dimension via a linear transformation:

$$\mathbf{q} = \mathbf{W}q\bar{\mathbf{h}}\mathrm{TCN} + \mathbf{b}_{q} \tag{17}$$

$$\mathbf{K} = \mathbf{W}_{k}\mathbf{E}^{\top} + \mathbf{b}_{k} \tag{18}$$

$$\mathbf{V} = \mathbf{W}_{v}\mathbf{E}^{\top} + \mathbf{b}_{v} \tag{19}$$

where, $\mathbf{W}_{q} \in \mathbb{R}^{d_a \times d_h}$, $\mathbf{W}_{k}, \mathbf{W}_{v} \in \mathbb{R}^{d_a \times d_b}$ are weight matrices, $\mathbf{b}_q$, $\mathbf{b}_k$, $\mathbf{b}_v$ are the corresponding bias vectors $\mathbf{K}, \mathbf{V} \in \mathbb{R}^{d_a \times T}$.

Subsequently, the similarity between the query and all keys is computed, and the attention weights $\boldsymbol{\alpha}$ are obtained by normalising the result through the Softmax function:

$$\boldsymbol{\alpha} = \mathrm{Softmax}\left(\frac{\mathbf{q}^{\top}\mathbf{K}}{\sqrt{d_a}}\right) \tag{20}$$

where, $\boldsymbol{\alpha} \in \mathbb{R}^T$ represents the importance of the lyrics of the t^{th} song to the current listening sequence context, where each element α_t corresponds to this importance. $\sqrt{d_a}$ is a scaling factor used to prevent gradient vanishing caused by excessively large inner products.

Weight the values using attention weights and perform a weighted summation to obtain an enhanced semantic representation **c** filtered based on temporal context:

$$\mathbf{c} = \mathbf{V}\boldsymbol{\alpha}^{\top} \tag{21}$$

Finally, we concatenate the raw global temporal features $\bar{\mathbf{h}}_{\text{TCN}}$ with the attention-weighted semantic context vector **c**. This concatenated input is then fed through a fully connected layer for fusion and dimensionality reduction, yielding the final joint representation **z**:

$$\mathbf{z} = \text{ReLU}\left(\mathbf{W}f[\bar{\mathbf{h}}\text{TCN}; \mathbf{c}] + \mathbf{b}_f\right) \tag{22}$$

where, [;] denotes vector concatenation, and $\mathbf{W}_f$ and $\mathbf{b}_f$ are the parameters of the fusion layer.

3.6 Model training and loss function

Inputting the joint representation **z** into a simple Softmax classifier yields a probability distribution over *C* mental health categories:

$$\hat{\mathbf{y}} = \text{Softmax}\left(\mathbf{W}_c\mathbf{z} + \mathbf{b}_c\right) \tag{23}$$

where, $\hat{\mathbf{y}} \in \mathbb{R}^C$, $\mathbf{W}_c$ and $\mathbf{b}_c$ are the parameters of the classifier.

We employ cross-entropy loss as the objective function for model training to measure the discrepancy between the predicted distribution $\hat{\mathbf{y}}$ and the true labels *y* (one-hot encoded):

$$\mathcal{L}\text{CE} = -\sum c = 1^C y_c \log\left(\hat{y}_c\right) \tag{24}$$

To prevent overfitting, we incorporate an L2 regularisation term (weight decay) into the loss function, constraining all trainable parameters Θ of the model (excluding pre-trained BERT parameters):

$$\mathcal{L} = \mathcal{L}_{\text{CE}} + \lambda \,|\, \Theta \,|_2^2 \tag{25}$$

Among these, λ is the hyperparameter controlling the regularisation strength. The model undergoes end-to-end training using the adaptive moment estimation (Adam) optimiser by minimising the total loss $\mathcal{L}$. During training, the parameters of the BERT model are frozen, with only the parameters of the remaining modules updated to stabilise training and conserve computational resources.

Algorithm TCN-LM model training algorithm

Input: Training dataset $D=\{(S_i,L_i,y_i)\}_{i=1}^{N}$, TCN hidden layer dimension d_h, attention mechanism dimension d_a, learning rate η, batch size B, maximum training epoch E, L2 regularisation coefficient λ

Output: Trained model parameters Θ

```
Initialise TCN module parameters $\theta_{\text{TCN}}$
Initialise fusion module parameters $\theta_{\text{fusion}}$
Load the pre-trained BERT model and freeze its parameters.

for epoch =1 to $E$ do
    for each small batch $\{(S_b, L_b, y_b)\}$ in $D$ do

        // Forward propagation
        for $k$ =1 to $B$ do
            // TCN temporal feature extraction
            $\mathbf{X}_k$ = Embedding ($S_b[k]$) → Sequence embedding
                $\mathbf{H}_{\text{TCN}}^{k} = \text{TCN}(\mathbf{X}_k)$ →Time-series feature extraction
            $\bar{\mathbf{h}}_{\text{TCN}}^{k} = \text{AveragePooling}(\mathbf{H}_{\text{TCN}}^{k})$ → Global sequential representation

            // Semantic encoding in language models
                $\mathbf{E}_k$ = BERT($L_b[k]$) → Semantic feature extraction
            $\bar{\mathbf{h}}_{\text{LM}}^{k} = \text{AveragePooling}(\mathbf{E}_k)$ → Global semantic representation

            // Cross-modal fusion
            $\mathbf{c}_k = \text{CrossModalAttention}(\bar{\mathbf{h}}_{\text{TCN}}^{k}, \mathbf{E}_k)$
            $\mathbf{z}_k = \text{FusionLayer}([\bar{\mathbf{h}}_{\text{TCN}}^{k}; \mathbf{c}_k])$
            $\hat{\mathbf{y}}_k = \text{Softmax}(\text{Classifier}(\mathbf{z}_k))$

            $\mathcal{L}_k = \text{CrossEntropyLoss}(\hat{\mathbf{y}}_k, y_b[k])$
        end for

        // Calculate batch loss
        $\mathcal{L}_{\text{batch}} = \frac{1}{B}\sum_{k=1}^{B}\mathcal{L}_k + \lambda\|\Theta\|_2^2$

        // Backpropagation
        $\nabla_{\Theta} = \frac{\partial \mathcal{L}_{\text{batch}}}{\partial \Theta}$

        // Parameter update
         $\Theta = \Theta - \eta$ AdamUpdate ($\nabla_{\Theta}$)

    end for

    // Validation set evaluation
    if epoch%10 == 0 then
        accuracy = EvaluateOnValidationSet()
        Print('Epoch', epoch, 'Validation Accuracy:', accuracy)
     end if

end for

return $\Theta$
```

4 Experiments and analysis

4.1 Experimental setup

4.1.1 Dataset and pre-processing

This study employs two publicly available datasets for experimental validation. Music listening data is sourced from the Last.fm-1K dataset, which contains complete music listening histories of approximately 1,000 anonymous users. This includes song IDs, artists, listening timestamps, and user-generated social tags such as 'chill,' 'depressing,' and 'energetic.' Mental health label data was sourced from a public subset of the myPersonality dataset, which contains psychology scale scores completed by users via a Facebook application. We selected the centre for epidemiologic studies depression scale (CES-D) scores as a proxy indicator for mental health status. After the thresholds of common clinical practices, we transformed scores on CES-D to a three-category nomenclature; we considered the scores near 15 and 23–33 (16–23) were the most common terms used in clinical practice; we regarded healthy (0 points), severe depressive (24 points and above), and mild depressive symptoms (16–23), to be present.

Through completion of association matching using user IDs (in accordance with ethical and anonymisation requirements of each dataset), we finally assembled an effective multimodal dataset of 3,852 users. We picked out the sequences of listening of each user over the past 6 months, and uniformly truncated or padded each sequence to a common length of T = 100. The choice of T = 100 as the uniform sequence length was informed by a balance between data representativeness and model practicality. Analysis of the user listening histories showed that this length covers a significant portion of recent listening activity for most users while remaining computationally manageable. We also conducted sensitivity analyses on a subset of data, confirming that lengths near 100 provided a stable trade-off between capturing sufficient temporal context and avoiding excessive padding or truncation artefacts. Textual information for each song was constructed by concatenating corresponding Last.fm social tags, serving as a supplement and alternative to lyrics (due to copyright restrictions on complete lyrics). The dataset was randomly split into training, validation, and test sets at a ratio of 7:1.5:1.5. Detailed statistical information of the dataset is shown in Table 1.

Table 1 Dataset statistics

Statistical item	Numerical value
Total number of users	3,852
Number of users in the training set	2,696
Number of users in the validation set	578
Test set user count	578
Average sequence length (first song)	87.4
Health (category 0) user proportion	58.3%
Proportion of users with mild symptoms (category 1)	28.1%
Proportion of users with severe symptoms (category 2)	13.6%

4.1.2 Comparison algorithms and evaluation metrics

To comprehensively evaluate the performance of the proposed model (denoted as TCN-LM), we compared it against several representative baseline methods, all of which were reproduced according to their original papers:

- LSTM-audio: a model based on LSTM networks that utilises Mel-frequency cepstral coefficients features extracted from audio signals as input. It is a classic temporal model in the field of music emotion recognition.
- BERT-text: utilises only song tag text to obtain document-level embeddings via a pre-trained BERT model, which are then fed into a fully connected layer for classification. This represents a purely semantic approach.
- Early fusion: an early fusion strategy that concatenates the features from the final hidden layer of the LSTM-Audio model with the document embeddings from BERT-text, followed by classification.
- Late fusion: a late fusion strategy that performs a weighted average of the prediction probabilities from the LSTM-Audio and BERT-Text models, with the weights determined through optimisation on the validation set.

The measures of evaluation that will be used are accuracy, macro-averaged F1-score (Macro-F1) score, and weighted average area under the curve (AUC). The macro-F1 score provides a fair assessment of model performance on data with class imbalance, while the weighted average AUC comprehensively evaluates classification performance across different categories.

4.1.3 Implementation details

Our TCN-LM model is implemented using the PyTorch framework. The TCN module comprises four residual blocks, each with a hidden dimension of 128, a convolution kernel size K = 3, and a dilation factor that increases exponentially with layer number. The language model module utilises a pre-trained BERT-base-uncased model with an output dimension $d_b = 768$. The cross-modal attention dimension d_a is set to 256. During training, BERT parameters are frozen. We adopted a strategy of freezing the pre-trained BERT parameters after comparative experiments showed that fine-tuning offered negligible performance gains on our specific task, while considerably increasing the risk of overfitting and training instability. Given that our downstream textual inputs (social tags) are relatively concise and aligned with general language, the frozen, general-purpose embeddings from BERT provided a robust and transferable semantic foundation, allowing the other model components to specialise in learning the multimodal interactions. The Adam optimiser is employed with an initial learning rate of 1e-3, subject to learning rate decay. The batch size is set to 32, and the L2 regularisation coefficient λ is fixed at 1e-4. All experiments are conducted on NVIDIA Tesla V100 graphics processing units.

4.2 Results and analysis

4.2.1 Primary experimental comparative analysis

The performance comparison results of different models on the test set are shown in Table 2. It can be seen that our proposed TCN-LM model achieves the best performance across all three evaluation metrics.

Table 2 Model performance comparison results

Model	*Accuracy rate*	*Macro F1 score*	*Weighted AUC*
LSTM-Audio	0.641	0.598	0.812
BERT-Text	0.668	0.623	0.834
Early Fusion	0.689	0.652	0.851
Late Fusion	0.701	0.665	0.863
TCN-LM (Ours)	0.734	0.704	0.892

The specific analysis is as follows: first, the performance of single-modal baseline models (LSTM-audio and BERT-text) is relatively limited, confirming the assertion in the introduction that relying solely on either temporal or semantic perspectives is insufficient. BERT-Text outperforms LSTM-Audio slightly, indicating that the semantic information embedded in user-provided social tags holds greater discriminative power than low-level audio features in this task. Second, the fusion baselines (early fusion and late fusion) both perform better than single-modal models, which are evidence of the utility of multimodal fusion. But their merging processes are still quite rough-grained, and cannot reach profound interaction between modalities. Finally, our TCN-LM model compares significantly to any of the baselines where long sequence dependencies are modelled with TCN architecture that is more expressive, and cross-modal attention that is used to perform dynamic feature selection and fusion. As an example, TCN-LM was more accurate than the best baseline (late fusion) by 3.3% and it had a higher macro F1 score by 3.9% points which is a clear indication that our proposed architecture is the best.

4.2.2 Melting experiment

In order to analyse the role of each part in the model, we a had a systematic ablation experiment, where the results are presented in Table 3.

Table 3 Melting experiment results

Model variants	*Accuracy rate*	*Macro F1 score*	*Weighted AUC*
TCN-LM (full model)	0.734	0.704	0.892
W/o TCN (replaced with LSTM)	0.705	0.668	0.865
W/o LM (TCN only)	0.652	0.607	0.828
W/o attention (replace with concatenation)	0.716	0.685	0.878

- W/o TCN: when one substituted the temporal feature extraction module with an LSTM with the same number of layers, there was a considerable decrease in performance. This confirms that TCN has a superiority to the conventional RNN architectures in its ability to capture long-term dependencies in music listening because its parallelisation and increased effective receptive field give greater strength in sequence modelling.
- W/o LM: removing the language model module process and instead only processing the sequence IDs by TCN caused a significant drop of performance to even below the BERT-Text baseline. This highlights the primary importance in this task of semantic/tag information of lyrics. The model has difficulty in semantically advising the listening behaviours unless some semantic guidance is provided.
- W/o attention: the substitution of the cross-modal attention fusion module with the straightforward concatenation of features caused a significant drop in the performance. This means that our programmed attention system is able to accomplish complementary modal exchange of information dynamically prioritising those semantic features most important to the temporal context at hand as opposed to attending to all features in an equal manner.

4.2.3 Explainability analysis

To explore on the foundation of the decision-making process in the model, we plotted the cross-modal attention weights of a test user case. The actual label of the user was a severe depressive symptoms, which the model gained correctly. Figure 2 illustrates some of the listening order and weights of attention observed by the user.

- Result analysis: It is clear in the figure that weight of attention is not distributed equally. The model gives more emphasis on a smaller number of songs, whose tags on Last.fm, when viewed, contain mostly words that are mostly linked to depressive moods, such as sad, melancholy, dark, and lonely, among others. On the other hand songs having low weight are those that have mostly been tagged as party, upbeat and dance. This proves that the model has been able to learn a meaningful, understandable pattern: in the process of recognising users with signs of depression, the machine is automatically inclined to pay attention to emotional music tracks rated negatively in their listening history and ignore positive ones. This is according to the rationality of clinical diagnosis in the human brain, enhancing good transparency in the creative aspect of the model.

Figure 2 Testing the cross-modal attention weight distribution of the user listening sequence (see online version for colours)

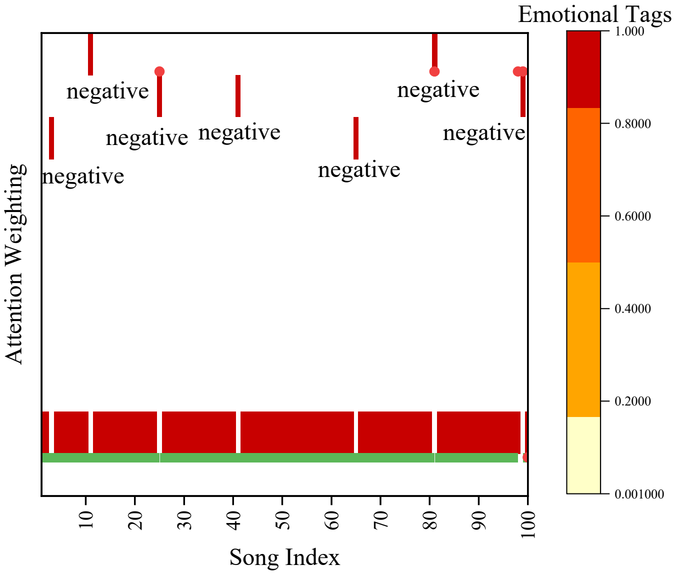
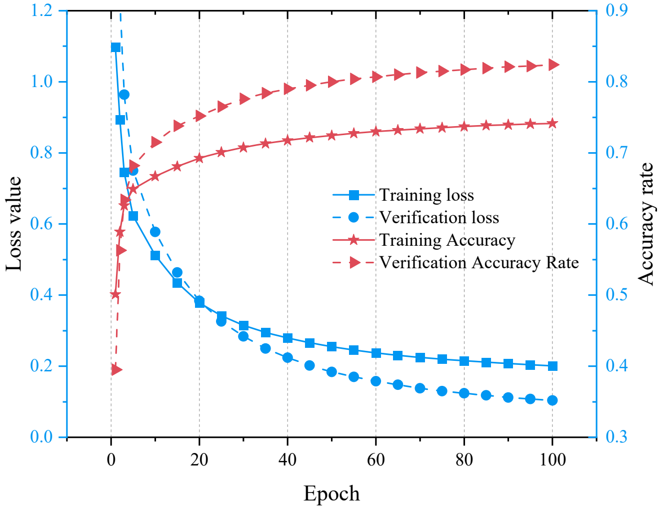


Figure 3 Loss and accuracy curves during TCN-LM model training (see online version for colours)



4.2.4 Training dynamic analysis

Figure 3 demonstrates the curves of loss and accuracy of TCN-LM model as it is being trained over training and validation sets.

- Result analysis: the curve shows that the loss of training occurs in a straight line fashion as more epochs are run and the training accuracy also increases in line with it. The loss and the accuracy on the validation set are almost similar to that of the training set and no sharp deviation is noticed during the training process. This is an indication that we have a stable and convergent model training process. The two L2 regularisation and fixed BERT strategies used manage to address overfitting and successfully guarantee the generalisation ability of the model.

5 Conclusions

This paper fills available gaps in music preference-based mental health decoding paradigms in time dynamic modelling and multimodal information deep integration framework by presenting a new paradigm, integration of TCNs and language models. You can see that using our proposed TCN-LM model, systematic validation on a real-world multimodal sample of 3852 users shows significantly higher performance compared to Alternate baseline algorithms, with an accuracy of 73.4 and macro F1 score of 0.704. More importantly, core component experiments demonstrate the efficiency of the core components: TCN module is more effective than traditional LSTMs in capturing long-term listening dependencies, whereas cross-modal attention dynamically extracts essential semantic information to obtain better modality synergy as opposed to the simple fusion approaches. The explainability analysis also demonstrates the rationality of decision-making process of the model. Its attention weights adjust themselves automatically to preferences of emotive musical media that are very much correlated with a psychological emotion like depression and anxiety, which offer a solid argument in terms of validity of the model.

This paper has theoretical contributions that are two-fold. First, it methodologically confirms the practicality and excellence of directly integrating TCNs into language model pre-trained with pre-trained language models, offers a framework such as generalisation on resolving similar temporal-semantic multimodal problems. Second, the study can be used to reveal preliminary dynamic and fine-grained correlates between the patterns of music listening and mental health state by taking advantage of intelligible attention mechanisms. This enhances our comprehension of the ability of the Digital behavioural footprints to mirror the state of underlying psychological condition and this provides new insight into computational behavioural science.

At the less abstract level, this work provides the technical background of the creation of the brand-new generation of non-invasive, dynamic, and affordable mental health screening devices. The suggested model could be incorporated into the current music streaming services or apps connected with health. It can predict upcoming mental health dangers early and dynamically by examining analysed dynamic aggregated and anonymised listening patterns. Moreover, the types of music identified by the model that have significant correlations with particular states of the psyche can be used as the sources of data-based references when creating personalised intervention programs in the music therapy.

Naturally, this research has its shortcomings as well. To begin with, the data are obtained through publicly available sources, and its mental health identifiers are based on self-reporting measures. These results have to be confirmed in future work by utilising more clinical representative samples. Second, the model now mainly operates on text and sequence id data and is yet to combine the original audio cue. In the future, we will consider instant models that are more complex and multifaceted, that is, they integrate audio, lyrics, and listening context, as well as investigate the generalisation ability of the model to other cultures and demographics. At the same time, user data privacy and security in usable applications, as well as development of ethically impermissible deployment processes, is an important issue that still needs to be discussed to promote the practical implementation of this technology.

Declarations

All authors declare that they have no conflicts of interest.

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