Computers and Electrical Engineering 114 (2024) 109071

Contents lists available at ScienceDirect

Computers and Electrical Engineering

journal homepage: www.elsevier.com/locate/compeleceng

TAM-SenticNet: A Neuro-Symbolic AI approach for early depression detection via social media analysis

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ARTICLE INFO

Keywords:
Neuro-Symbolic AI
Depression detection
Social media analysis
Early intervention
Sentiment analysis

ABSTRACT

This paper introduces TAM-SenticNet, a Neuro-Symbolic AI framework uniquely designed for early depression detection through social media content analysis. Merging neural networks for feature extraction and sentiment analysis with advanced symbolic reasoning, TAM-SenticNet overcomes the limitations of traditional diagnostic tools, particularly in real-time responsiveness and interpretability. The symbolic reasoning, powered by SenticNet, provides a deep, structured understanding of emotional expressions, greatly enhancing model explainability and logical inference. Empirical evaluations reveal that TAM-SenticNet excels beyond existing models in performance metrics, achieving a Precision of 0.665, Recall of 0.881, and F_1-score of 0.758, coupled with superior latency metrics, including $ERDE_5$ and $ERDE_{50}$ at 0.025, $Latency_{TP}$ at 1.0, and $F_{latency}$ at 0.675. These achievements highlight TAM-SenticNet's cutting-edge approach to early depression detection, making it a pioneering tool in the application of AI for mental health informatics.

1. Introduction

Depression, a significant public health challenge, impacts individuals and society at large [1–3]. Early detection is vital for effective intervention [4]. Traditional diagnostic methods like the Hamilton Depression Rating Scale (HAMD) and Beck Depression Inventory (BDI) are crucial but have limitations, including episodic assessment and reliance on self-reporting, which may miss early or subtle signs [5]. In contrast, social media offers a continuous, real-time mental health monitoring platform, providing insights into emotional states overlooked by traditional methods [6–8].

Recent AI-driven approaches in depression detection have evolved across neural, symbolic, and hybrid methodologies. Neural models excel in pattern recognition but often lack interpretability and struggle with nuanced emotional analysis [9,10]. Symbolic models offer structured reasoning and interpretability but can lack adaptability to complex datasets [11,12]. Hybrid approaches attempt to balance these aspects but still face challenges in real-time processing and comprehensive emotional understanding [13,14].

TAM-SenticNet, our Neuro-Symbolic AI framework, addresses these challenges. It combines neural networks' sentiment analysis capabilities with symbolic reasoning's logical inference, providing nuanced interpretations of emotional expressions in social media data. This approach not only overcomes the limitations of traditional methods but also harnesses the dynamic capabilities of social media analytics, setting a new standard in mental health research.

The main contributions of this paper are as follows:

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https://doi.org/10.1016/j.compeleceng.2023.109071
Received 1 October 2023; Received in revised form 28 December 2023; Accepted 30 December 2023
Available online 20 January 2024
0045-7906/

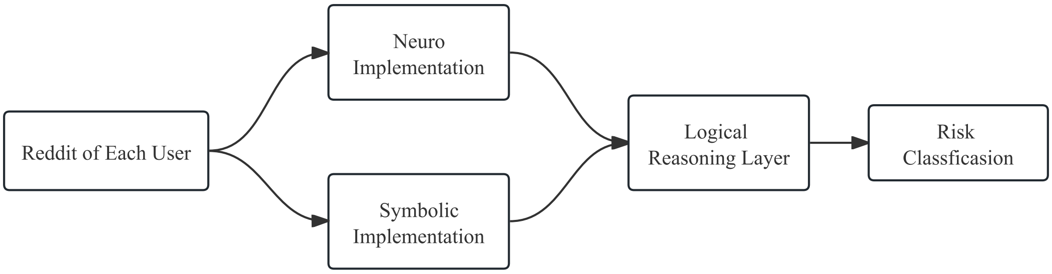

Fig. 1. Schematic overview of the TAM-SenticNet framework, illustrating the seamless integration of Neural and Symbolic Implementation modules for early depression detection.

- Development of TAM-SenticNet, a cutting-edge Neuro-Symbolic AI framework tailored for early depression detection through social media data analysis, merging neural network efficiency with symbolic reasoning.
- Comprehensive evaluation of TAM-SenticNet against established models, demonstrating its enhanced performance in Precision, Recall, and F_1, as well as Latency Metrics.
- Illustration of TAM-SenticNet's practical application potential, establishing a new benchmark in mental health informatics.

The remainder of this paper is organized as follows: Section 2 presents a literature overview, Section 3 outlines our experimental design and methodology, Section 4 discusses our findings, and Section 5 considers the broader implications of our research.

2. Related work

2.1. Traditional methods and clinical assessments

Early depression detection has traditionally involved both academic research and clinical practice, primarily using tools like the HAMD and BDI. Although essential, these methods have limitations in detecting subtle signs of depression [15–19]. Innovations in biological methods provide insights, yet their complexity and individual variability pose challenges [18,20–23]. TAM-SenticNet transcends these traditional methods by utilizing real-time social media data, enabling a dynamic and continuous monitoring approach.

2.2. Machine learning and social media analysis

Machine learning's impact on mental health research, especially depression detection via social media, has been profound. Pioneering work by De Choudhury et al. [24] and Reece and Danforth [25] set a precedent for utilizing social media data. This trend continued with further advancements in word embeddings and topic extraction techniques [26,27]. Recent studies like those by Villatoro-Tello et al. [28] and Zhu et al. [29] have furthered this domain, exploring novel methods for depression detection. Similarly, in the field of industrial diagnostics, machine learning has shown promising results, as demonstrated by [30] on machinery fault diagnosis. TAM-SenticNet builds on these advancements, integrating neural and symbolic AI for a more nuanced analysis.

2.3. Neuro-Symbolic AI in mental health research

The fusion of neural networks and symbolic reasoning in Neuro-Symbolic AI has seen growing applications in various domains, including mental health [31,32]. Studies by Garcez et al. [33,34] and Daniele and Serafini [35] highlight the integration of machine learning with automated reasoning. In the realm of mental health, TAM-SenticNet leverages these neuro-symbolic principles, combining deep learning with symbolic AI to enhance interpretability and decision-making transparency, addressing gaps in traditional models [36–38].

3. Neuro-Symbolic AI for early depression detection

To investigate the temporal dynamics of user affective states for the early identification of depression, we present TAM-SenticNet, a specialized Neuro-Symbolic AI framework, as depicted in Fig. 1. This framework comprises two principal modules: the Neural Implementation and the Symbolic Implementation.

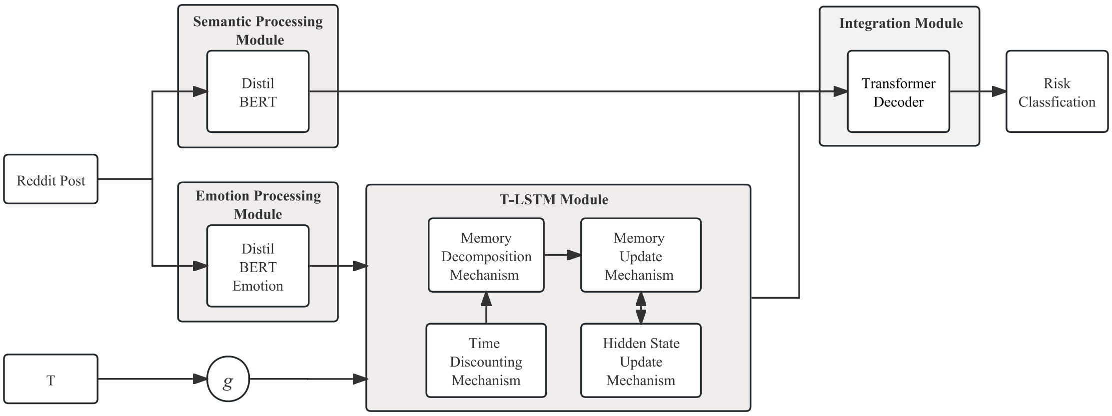

Fig. 2. Architectural design of the Time-Aware Affective Memories (TAM) network, showcasing its four core components: the Emotion Processing Module, the Time-Aware Long Short-Term Memory (T-LSTM) Module, the Semantic Processing Module, and the Integration Module.

3.1. Neural Implementation

Drawing inspiration from the work of Kang et al. [14] on the Time-Aware Affective Memories (TAM) network, our framework is a comprehensive system comprised of four integral modules: the Emotion Processing Module, the Time-Aware Long Short-Term Memory (T-LSTM) Module, the Semantic Processing Module, and the Integration Module. Together, these modules enable a sophisticated Neuro-Symbolic AI approach for accurately classifying depression risks, as illustrated in Fig. 2.

Emotion Processing Module: This module processes the emotional content of a user's latest post. It encodes the post into an affective state A_t based on a pre-trained DistilBERT Emotion classification model[1]:

$$A_t = \varphi\left(\mathrm{DistilBERT}_E(x_t)\right), \tag{1}$$

where x_t is the latest post, and $\varphi(\cdot)$ is a pooling operation.

T-LSTM Module: The T-LSTM Module is responsible for storing and updating the historical emotional states of a user. It processes the affective state A_t and uses a Time-Aware LSTM network to maintain the user's emotional trajectory over time. The T-LSTM network operates through the following mechanisms:

Memory Decomposition Mechanism: Decomposes the previous internal memory C_{t-1} into short-term and long-term components, where W_d and b_d are learnable parameters:

$$C^S_{t-1} = \tanh(W_d C_{t-1} + b_d) \quad \text{(Short-term memory)}$$
$$C^L_{t-1} = C_{t-1} - C^S_{t-1} \quad \text{(Long-term memory)}$$

Time Discounting Mechanism: Modulates the short-term memory based on the time interval $\Delta\tau_t = T_t - T_{t-1}$, attenuating the influence of older emotional states, with $g(\cdot)$ being a discount function applied to the short-term memory:

$$\hat{C}^S_{t-1} = C^S_{t-1} \times g(\Delta\tau_t) \quad \text{(Discounted short-term memory)}$$

Memory Update Mechanism: Updates the internal memory C_t by combining the current affective input A_t with the adjusted previous memory, where W_f, W_i, W_c, U_f, U_i, U_c, b_f, b_i, and b_c are learnable parameters:

$$C^A_{t-1} = C^L_{t-1} + \hat{C}^S_{t-1} \quad \text{(Adjusted previous memory)}$$

$$f_t = \sigma(W_f A_t + U_f h_{t-1} + b_f) \quad \text{(Forget gate)}$$

$$i_t = \sigma(W_i A_t + U_i h_{t-1} + b_i) \quad \text{(Input gate)}$$

$$\tilde{C}_t = \tanh(W_c A_t + U_c h_{t-1} + b_c) \quad \text{(Candidate current memory)}$$

$$C_t = f_t \times C^A_{t-1} + i_t \times \tilde{C}_t \quad \text{(Current memory)}$$

[1] https://huggingface.co/bhadresh-savani/distilbert-base-uncased-emotion.

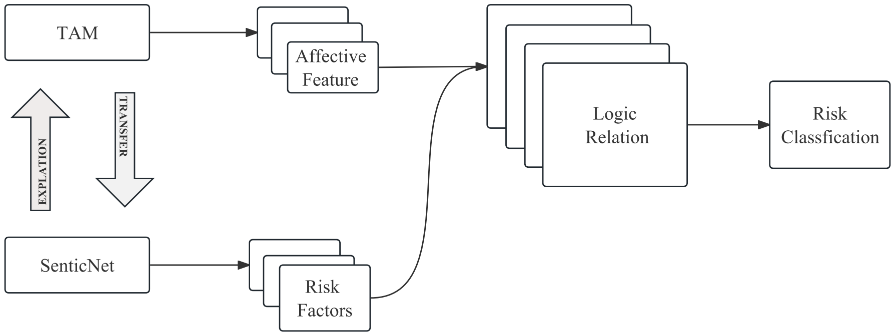

Fig. 3. Symbolic Implementation utilizing SenticNet as the reasoning engine, emphasizing how symbolic logic and semantic relations contribute to enhanced model interpretability.

Hidden State Update Mechanism: Updates the hidden state h_t, reflecting the latest emotional state of the user:

$$h_t = o_t \times \tanh(C_t) \qquad \text{(Current hidden state)}$$

Affective Memory Mechanism: To enrich the memorization of a user's affective states, the T-LSTM Module concatenates the most recent l_{MEM} affective memories, forming the enriched affective memory $\hat{M}_t$:

$$\hat{M}_t = \mathrm{Concat}(M_{t-l_{\mathrm{MEM}}+1}, \ldots, M_t), \tag{2}$$

where $\hat{M}_t$ represents the enriched affective memory, capturing a comprehensive emotional profile of the user over time.

Semantic Processing Module: This module focuses on capturing the semantic essence of each post. It converts the textual content of the post into a semantic embedding S_t using a pre-trained DistilBERT model[2]:

$$S_t = \mathrm{DistilBERT}(x_t), \tag{3}$$

where S_t represents the semantic embedding of the post.

Integration Module: The Integration Module fuses the enriched affective memory $\hat{M}_t$ from the T-LSTM Module with the semantic embedding S_t from the Semantic Processing Module. This fusion is executed using a Transformer Decoder:

$$H_t = \mathrm{TransformerDecoder}(\hat{M}_t, S_t), \tag{4}$$

where $\hat{M}_t$ is the enriched affective memory, and S_t is the semantic embedding. The result, H_t, is the integrated profile used for risk prediction.

The Neural Implementation, encompassing these four modules, effectively classifies depression risks, contributing to the overall efficacy of our Neuro-Symbolic AI framework in early depression detection.

3.2. Symbolic Implementation

To mitigate the interpretability challenges commonly associated with neural networks, we integrate SenticNet [39] as our symbolic reasoning engine. SenticNet functions as a sentiment knowledge repository, utilizing symbolic logic and semantic relations to furnish a structured emotional understanding, thereby augmenting the framework's interpretability. The architecture and functionality of this symbolic reasoning engine are visually depicted in Fig. 3, emphasizing its role in enhancing model interpretability.

Our framework synergistically fuses the outputs from the neural network with symbolic knowledge to deliver higher-order explanations and predictions. The Risk Factors identified by SenticNet are graphically represented in Fig. 4, which also delineates the logical interconnections among these factors. For example, an individual manifesting TakeSleepingPills, Irritability, and AttemptSuicide is highly likely to be at elevated risk for depression.

In our framework, we exploit both the neural network capabilities of TAM and the symbolic reasoning of SenticNet to evaluate a user's depression risk based on linguistic features. Fig. 5 elucidates the logical nexus between user language patterns and depression risk factors, thereby highlighting the synergistic interplay between SenticNet and TAM.

This logical diagram serves to illuminate the collaborative strength between SenticNet and TAM. Through this integrated methodology, we aspire to identify early indicators of depression with enhanced accuracy and efficiency, thereby enabling more timely professional interventions and improving mental health outcomes.

[2] https://huggingface.co/distilbert-base-uncased.

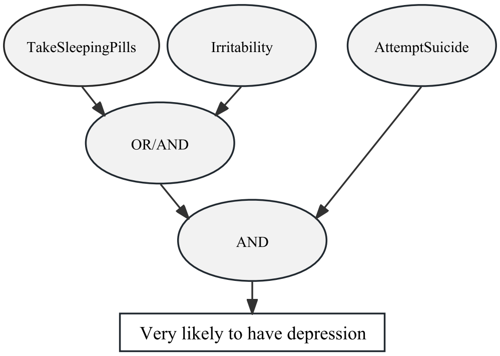

Fig. 4. Visual representation of Risk Factors as delineated by SenticNet, illustrating the logical interconnections among TakeSleepingPills, Irritability, and AttemptSuicide.

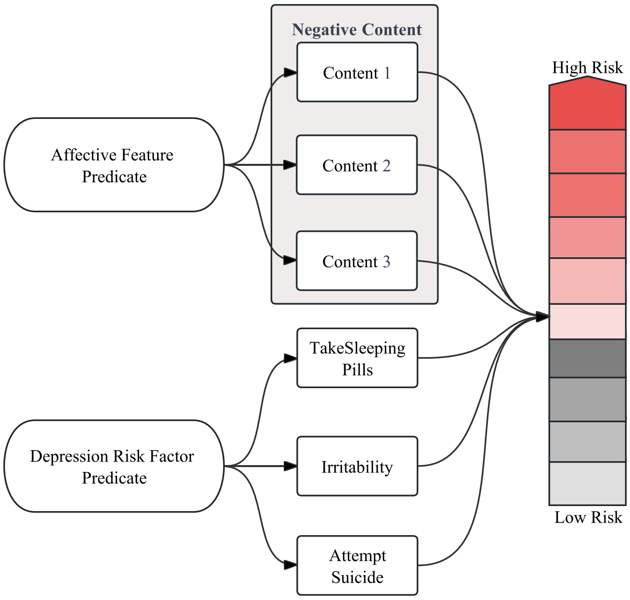

Fig. 5. Logical Relationship diagram illustrating the collaborative efficacy between SenticNet and TAM in assessing depression risk based on user language and emotional states.

Table 1
Positive and negative samples in CLEF eRisk 2017 and 2018 labs.

Year	Positive samples	Negative samples
2017	135	752
2018	79	741
Aggregate	214	1493

4. Experiment and results

4.1. Experimental data

The dataset employed in this research for early depression identification is sourced from the CLEF eRisk 2022 Lab. This dataset amalgamates both the training and testing sets from the CLEF eRisk 2017 Lab, in addition to the testing set from the CLEF eRisk 2018 Lab. A comprehensive overview of the dataset's attributes is presented in Table 1.

4.2. Evaluation metrics

4.2.1. Classification metrics: Precision, Recall, and F_1 score

In our early depression identification framework, we utilize essential classification metrics for a balanced evaluation: Precision, Recall, and the F_1 Score. Precision, defined as $\mathrm{Precision} = \frac{\mathrm{TP}}{\mathrm{TP+FP}}$, measures the model's accuracy in identifying true depression instances, with TP and FP denoting True Positives and False Positives, respectively. Recall, calculated as $\mathrm{Recall} = \frac{\mathrm{TP}}{\mathrm{TP+FN}}$, assesses the model's ability to capture genuine depression cases, where FN represents False Negatives. The F_1 Score, given by $F_1 = \frac{2\times(\mathrm{Precision}\times\mathrm{Recall})}{\mathrm{Precision}+\mathrm{Recall}}$, provides a harmonic mean of Precision and Recall, offering a comprehensive metric that considers both types of classification errors.

4.2.2. Latency metrics: ERDE, $\mathrm{Latency}_{TP}$, and $F_{latency}$

Timeliness constitutes another pivotal dimension in the domain of early depression identification. To address this, we deploy a suite of latency metrics—ERDE, $\mathrm{Latency}_{TP}$, and $F_{latency}$—to assess the model's efficacy and efficiency in real-time decision-making.

The ERDE metric amalgamates both the efficacy and timeliness of a decision by accounting for the relative costs of false negatives and false positives. It is mathematically formulated as

$$\mathrm{ERDE}_o = \frac{1}{N}\sum_{i=1}^{N}\left(c_{\mathrm{FN}} \times \mathrm{FN}_i \times \phi(o, k_i) + c_{\mathrm{FP}} \times \mathrm{FP}_i\right), \tag{5}$$

where N denotes the total number of instances, and c_{FN} and c_{FP} represent the costs of false negatives and false positives, respectively.

$\mathrm{Latency}_{TP}$ quantifies the median quantity of textual items required to accurately discern a true positive instance. It is mathematically expressed as

$$\mathrm{Latency}_{TP} = \mathrm{median}\{k_u : u \in \mathrm{U}, d_u = g_u = 1\}, \tag{6}$$

where U signifies the set of users and k_u indicates the number of textual items for user u [40].

$F_{latency}$ integrates the F_1 Score with a latency penalty term, striving to harmonize the model's accuracy and timeliness in the context of early depression detection. It is mathematically defined as

$$F_{latency}(\mathrm{U}, \mathrm{sys}) = F_1(\mathrm{U}, \mathrm{sys}) \times \left(1 - \mathrm{median}_{u\in \mathrm{U}\wedge \mathrm{ref}(u)=+} P_{latency}(u, \mathrm{sys})\right), \tag{7}$$

where U denotes the set of users, sys refers to the depression detection system under evaluation and $P_{latency}$ represents the proportion of true positives that are identified within the latency period [41].

4.3. Experimental results and discussion

4.3.1. Baseline models

We compare TAM-SenticNet's performance with various baseline models, each characterized by their core approach — neural, symbolic, or a combination of both. These models, documented in the eRisk survey paper [42], include:

Neural Models: CYUT (CY), **BLUE (BL)**, and **SCIR2 (SC)** employ advanced deep learning architectures for user-level classification. **LauSAn (LS)** and **NITK-NLP2 (NK)** utilize dynamic neural network analysis.
Symbolic Models: BioInfo_UAVR (BU) and **NLPGroup-IISERB (NI)** use classical machine learning with feature engineering. **E8-IJS (E8)** focuses on Logistic Regression models with varied input representations.
Hybrid Models: TUA1 (T1) and **UNSL (UN)** integrate neural techniques with feature-centric symbolic approaches. **RELAI (RL)** combines pre-trained word vectors with feature sets for automatic questionnaire population. **UNED-MED (UM)** incorporates tf-idf and sentiment analysis with a Deep Learning classifier. **Sunday-Rocker2 (SR)** adopts a multifaceted approach with tf-idf, linguistic features, and machine learning algorithms.

4.3.2. Results and discussion

In our study, TAM-SenticNet (TS) exhibits high Precision (0.665) and F_1 (0.758), demonstrating its effectiveness in accurately and comprehensively identifying depression cases as detailed in Table 2. This performance is particularly notable when compared with neural models like CY, BL, and SC, which primarily focus on deep learning techniques. Unlike these models, TAM-SenticNet integrates symbolic reasoning, enabling more nuanced data interpretation.

Symbolic models like BU, NI, and E8 rely heavily on feature engineering. TAM-SenticNet surpasses these models in Precision and F_1, highlighting the advantage of combining symbolic reasoning with neural network robustness. This combination allows TAM-SenticNet to capture complex patterns in data without solely relying on feature engineering.

Hybrid models such as T1, UN, RL, UM, and SR attempt to balance neural and symbolic approaches. However, TAM-SenticNet's Neuro-Symbolic AI approach further optimizes this balance, as evidenced by its superior F_1 score (0.758), which is indicative of a well-rounded performance in both Precision and Recall aspects.

In latency metrics, TAM-SenticNet excels with the lowest ERDE_5 (0.035) and ERDE_{50} (0.025) scores, demonstrating its efficiency in early risk detection—a crucial aspect of mental health applications. The $\mathrm{Latency}_{TP}$ score (1.0) and the highest $F_{latency}$ score (0.675)

Table 2
Comparative metrics of our **TAM-SenticNet (TS)** and other models.

Model	Prc	Rcl	F_1	E_5	E_{50}	L_{TP}	F_l
CY[a]	0.142	0.918	0.245	0.082	0.041	8.0	0.239
BL[a]	0.106	**1.000**	0.192	0.074	0.048	4.0	0.190
SC[a]	0.274	0.847	0.460	0.045	0.031	3.0	0.411
LS[a]	0.201	0.724	0.315	0.039	**0.025**	**1.0**	0.315
NK[a]	0.149	0.724	0.248	0.049	0.039	2.0	0.247
BU[b]	0.378	0.857	0.525	0.069	0.031	16.0	0.494
NI[b]	0.653	0.500	0.566	0.067	0.046	26.0	0.511
E8[b]	0.242	0.959	0.387	0.068	0.036	20.5	0.357
T1[c]	0.159	0.959	0.271	0.052	0.036	3.0	0.270
UN[c]	0.144	0.929	0.249	0.055	0.035	3.0	0.247
RL[c]	0.085	0.847	0.155	0.114	0.092	51.0	0.125
UM[c]	0.084	0.163	0.111	0.079	0.078	251.0	0.028
SR[c]	0.108	**1.000**	0.195	0.082	0.047	6.0	0.191
TS	**0.665**	0.881	**0.758**	**0.035**	**0.025**	**1.0**	**0.675**

Model types are indicated as follows:
[a] For Neural Models.
[b] For Symbolic Models.
[c] For Hybrid Models.

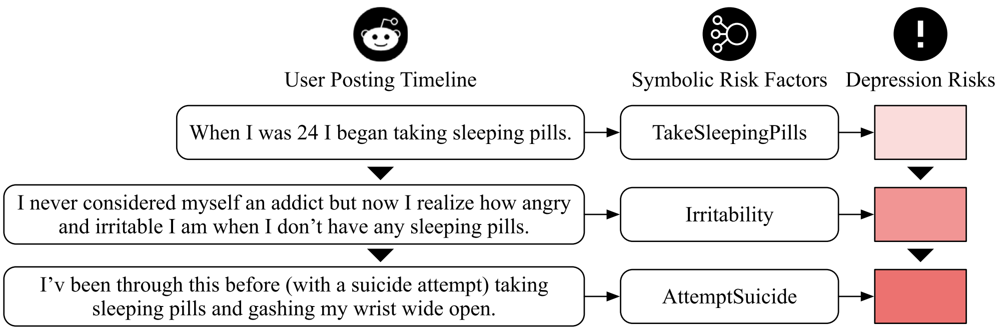

Fig. 6. TAM-SenticNet's symbolic reasoning applied to a Reddit user's posts. The model discerns risk factors—"TakeSleepingPills", "Irritability", and "AttemptSuicide"—to evaluate evolving depression risk levels from medium to very high.

further establish TAM-SenticNet as a model that proficiently balances timely and accurate detection. These metrics are especially important in early depression detection, where prompt intervention can significantly alter outcomes.

These findings strongly advocate for the integration of neural networks and symbolic reasoning in TAM-SenticNet, marking a significant stride in mental health informatics. Its capability to accurately, promptly, and efficiently detect early signs of depression, leveraging the strengths of both neural and symbolic methodologies, positions it as a highly promising tool in this critical field of research. The comprehensive evaluation against various model types underscores TAM-SenticNet's potential to set a new benchmark in early depression detection.

4.3.3. Case study: Symbolic reasoning in action

To further illuminate the capabilities of TAM-SenticNet in real-world applications, we present a case study that exemplifies how symbolic reasoning functions within the model. Fig. 6 delineates this by monitoring the fluctuating risk levels of depression for a Reddit user based on their posts.

Initially, the user posted, "When I was 24 I began taking sleeping pills". The symbolic reasoning component of TAM-SenticNet ascertained the risk factor "TakeSleepingPills", leading to a medium risk level of depression. Subsequently, the user articulated, "I never considered myself an addict but now I realize how angry and irritable I am when I don't have any sleeping pills". Here, the symbolic risk factor "Irritability" was identified, escalating the risk level to high. Finally, the user divulged, "I've been through this before (with a suicide attempt) taking sleeping pills and gashing my wrist wide open". The model discerned the symbolic risk factor "AttemptSuicide", culminating in a very high risk of depression. These risk assessments are derived from the logical relations delineated in the symbolic implementation of TAM-SenticNet, highlighting the model's capacity for nuanced and precise estimations.

For additional examples demonstrating TAM-SenticNet's application in a wider range of scenarios, please refer to the case studies provided in the Appendix. These cases further exemplify the model's versatility and effectiveness in analyzing various emotional and linguistic patterns indicative of depression risk.

Table A.3
Case studies of symbolic reasoning in TAM-SenticNet.

Reddit post	Reasoning steps
I always **feel unloved**. Every single day I **get closer to suicide**. "**I want to die**" is my first thought of the morning or after I nap. I have **no hope or will to live**... I have mental breakdowns every single day.	"feel unloved" → SocialIsolation; "I want to die" → AttemptSuicide; "get closer to suicide" → AttemptSuicide; "no hope or will to live" → ProlongedSadness; SocialIsolation ∧ AttemptSuicide ∧ ProlongedSadness → Depressed (6)
I love them more than the moon and the stars... It has caused me tremendous heartache... I feel like parenting just **beat the living shit out of me**. I have nothing left to give anybody... I'm emotionally and mentally bankrupt from it.	"beat the living shit out of me" → ProlongedSadness ∧ AnxietyAndWorry; ProlongedSadness ∧ AnxietyAndWorry → Depressed (4)
Hey, I've been on **Sertraline** for nearly two years...	"Sertraline" → SubstanceAbuse; SubstanceAbuse → Depressed (1)
I felt like I was putting in all the effort... I always knew he loved me, but I still **felt very lonely** in the relationship as it currently stood.	"felt very lonely" → AnxietyAndWorry; AnxietyAndWorry → Depressed (2)
I have **insomnia and anxiety** as well and may even have **hypomania**. A few weeks ago I was optimistic... And then I crashed and have been in what feels like a **never-ending depressive** episode since June.	"insomnia and anxiety" → SuddenBehavioralChange; "never-ending depressive" → ProlongedSadness; "hypomania" → ErraticBehavior; SuddenBehavioralChange ∧ ProlongedSadness ∧ ErraticBehavior → Depressed (5)
My mother has a bad knee... I have **always worried** that the same thing would happen to me...	"always worried" → AnxietyAndWorry ∧ ProlongedSadness; AnxietyAndWorry ∧ ProlongedSadness → Depressed (3)

5. Conclusion

This study introduces TAM-SenticNet, a groundbreaking Neuro-Symbolic Artificial Intelligence framework, as an efficacious instrument for the early detection of depression. Excelling in the integration of neural networks for feature extraction and sentiment analysis with symbolic reasoning for intricate logical inference, TAM-SenticNet has demonstrated superior performance across a comprehensive range of evaluation metrics, including Precision, Recall, F_1 score, $ERDE_5$, $ERDE_{50}$, $Latency_{TP}$, and $F_{latency}$. These findings position TAM-SenticNet as a potent tool in the realm of mental health informatics, offering promising prospects for its practical implementation.

Our future work will concentrate on augmenting TAM-SenticNet with medical expert knowledge from internationally recognized depression diagnosis manuals such as DSM-5-TR, ICD-11, and PHQ-9. This enhancement is envisioned to bolster the framework's clinical relevance and trustworthiness by aligning its analytical capabilities with established diagnostic criteria and best practices in mental health care. The integration of this expert knowledge is anticipated to not only refine the model's interpretability and accuracy but also to ensure that its output aligns with clinical insights, thus bridging the gap between AI-driven analysis and real-world clinical applications in depression detection and early intervention. Through these efforts, we aim to create a Neuro-Symbolic AI system that is not only technologically advanced but also deeply rooted in medical expertise, making it a valuable asset in the field of mental health.

Funding

This study was supported by the JSPS KAKENHI, Japan Grant Number 19H04215.

CRediT authorship contribution statement

Rongyu Dou: Conceptualization, Formal analysis, Writing – original draft, Writing – review & editing. **Xin Kang:** Conceptualization, Writing – review & editing.

Data availability

The authors do not have permission to share data.

Appendix. Symbolic reasoning examples

Table A.3 presents a series of case studies extracted from the testing set of the CLEF eRisk 2022 Lab dataset. These studies demonstrate the TAM-SenticNet framework's application in analyzing real-world social media content, particularly Reddit posts, to assess depression risk.

In the table, each entry includes the original Reddit post, with crucial negative expressions highlighted in bold. The "Reasoning Steps" column delineates TAM-SenticNet's logical process for determining depression risk from these posts. This column vividly illustrates the framework's ability to intricately analyze emotional and linguistic patterns. The risk level predicted by TAM-SenticNet is denoted in parentheses, on a scale from 1 to 10, where higher values indicate increased risk severity. This compilation of case studies underscores TAM-SenticNet's practical utility and effectiveness in detecting early signs of depression through the detailed examination of social media content.

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