From Detection to Discovery: A Closed-Loop Approach for Continuous Medical Knowledge Expansion and Depression Detection on Social Media

Online Supplementary Material

Appendix 1: Initial Knowledge graph Evaluation

To construct the depression diagnosis-related knowledge graph, we have drawn from widely recognized medical literature and depression clinical screening measures, including:

1. APA. DSM-5-TR(tm) Classification. American Psychiatric Association Publishing, 2022.

2. Beck, M.D.A.T. and Alford, P.D.B.A.Depression: Causes and Treatment. University of Pennsylvania Press, 2014.

3. Martin, A., Rief, W., Klaiberg, A., and Braehler, E. Validity of the Brief Patient Health Questionnaire Mood Scale (PHQ-9) in the general population. General Hospital Psychiatry, 28, 1 (January 2006), 71–77.

4. Rush, A.J., Trivedi, M.H., Ibrahim, H.M., et al. The 16-Item Quick Inventory of Depressive Symptomatology (QIDS), Clinician Rating (QIDS-C), and Self-report (QIDS-SR): A Psychometric Evaluation in Patients with Chronic Major Depression. Biological Psychiatry, 54, 5 (September 2003), 573–583.

To validate the constructed depression diagnosis-related knowledge graph, we employ a two-step validation process. The first step involves a medical knowledge coverage evaluation. The second step includes a medical expert evaluation. In the first step, the evaluation of medical knowledge coverage aims to involve assessing the ontology's coverage by comparing the number of concepts within the ontology to several commonly utilized depression diagnostic scales. The coverage results of the depression ontology with respect to DSM-5-TR, PHQ-9, and QIDS-SR are detailed in Table A1. The coverage calculations demonstrate that our ontology comprehensively encompasses the content of widely used depression scales.

Table A1. The Coverage Rate of Depression Ontology to Depression Diagnosis Scale

Depression diagnosis scales	**DSM-5-TR**	**PHQ-9**	**QIDS-SR**
Coverage rate	85.6%	95.2%	93.8%

In the second step of evaluation: medical expert assessment, we engaged a panel of medical experts. Two psychiatrists from a nationally recognized hospital were invited to evaluate our depression ontology. Following their initial independent reviews, the psychiatrists convened to include entities that were absent in the initial version while eliminating redundant and clinically irrelevant entities. Entity classes that were misassigned were corrected. The final ontology, approved by these medical experts, was employed in our study.

Appendix 2: Parameter Settings, Testing Data, and Knowledge Graph Pre-training

For the implementation of our method, we use PyTorch to build the proposed method. The embedding dimension of Relational Graph Neural Network with Hierarchical Attention (RGHAT) is set to 768, while that of the large language model (LLM) is set to 4096. The maximum sequence length is set to 100 for the depression-related entity recognition component and 200 for the depression detection module. For the other deep learning-based baseline algorithms, the maximum sequence length is set to 200. All deep learning benchmarks adopt the AdamW optimizer for parameter optimization, and the learning rate is set to 1e-4.

Table A2. Parameter Settings for Compared Methods

Model	**Parameter**	**Value**	**Model**	**Parameter**	**Value**
Choudhury et al. (2013)	Regularization parameter	1	LSTM-based (Khan et al., 2021)	Number of hidden units	256
	Kernel	Linear	LSTM-based (Khan et al., 2021)	Number of hidden units	500
Coppersmith et al. (2014)	Regularization parameter	1	Attention-based (Ghosh et al., 2023)	Number of hidden units of LSTM	128
	Solver	L-BFGS		Number of hidden units of CNN	32

Preotiuc-Pietro et al. (2015)	Regularization parameter	1	Attention-based (Thekkekara et al., 2024)	Number of hidden units of LSTM	128
	Solver	L-BFGS		Number of hidden units of CNN	128
Benton et al. (2017)	Number of hidden layers	2	Contrastive Learning-based (Liu et al., 2024)	Dynamic routing num	3
	Number of hidden units	[20, 10]		Number of hidden units	768
Reece et al. (2017)	Criterion	entropy	Transformer-based (Malviya et al., 2021)	Number of heads	12
	Number of estimators	750		Number of layers	10
				Number of hidden units	768
Chau et al. (2020)	Estimators	SVC + RF + MLP	JDeC (Ours)	Number of hidden units of RGHAT	768
CNN-based (Lin et al., 2020)	Conv 1/2/3 kernel size	[3, 4, 5]		Number of hidden units of LLM	4096
	Number of kernels	256		LoRA rank	4
	Pool	Max pool		LoRA alpha	8

The statistics of the testing dataset has been provided in Table A3.

Table A3. Dataset

	Depressed	Non-depressed
Number of posts	141,736	1,724,788
Number of words	4,244,173	48,002,886
Average number of posts per user	310	505
Average number of days from first to last post	620	621
Number of users	457	3413

The knowledge graph pre-training is detailed below. In the pre-training stage, the knowledge graph learns embeddings from labeled social media posts generated by clinically diagnosed depression patients on WebMD, a widely recognized online health information platform. On WebMD, patients discuss their depression symptoms, treatments, and life events, which are depression-related entities. This provides a foundation for modeling the social media behavior of depression patients. In a dataset previously used in existing research, depression-related entities in WebMD posts were manually labeled and validated by experts (Zhang et al. 2024). Additional labeling was conducted by inviting mental health professionals to classify depression-related entities into psychological symptoms and physical symptoms, and to further classify treatment-related entities into medication and therapy. Entities that co-occur within the same post are paired and connected using predefined relations, forming a set of triplets that serve as positive samples for entity embedding learning (as described in Section 3.1.2).

Appendix 3: The Algorithm for Entity Importance Estimation.

The algorithm for estimating entity importance in our proposed framework is presented in Algorithm A1.

Algorithm A1. Entity Importance Computation

Input: Depression knowledge graph G and an entity e_i
Output: The max transition probability p_{trans} as the importance value of e_i for depression prediction
Set e_i as the start node and $e_{depression}$ as the target node
Set the maximum transition path length as p_{length}
Set the number of Monte Carlo samples as $n_{samples}$
Procedure MonteCarlo_MaxTransProb(G, e_i, $e_{depression}$, p_{length}, $n_{samples}$):
    p_{trans} = 0
    For $i \leftarrow 1, \ldots, n_{samples}$ **do**
        current_node ← e_i
        $path\_probability$ ← 1.0
        $path\_length$ ← 0
        While not (current_node==$e_{depression}$ or $path\_length > p_{length}$) **do**
            $N_{current}$ ← the neighbor entities for current_node in G
            If $N_{current}$ is empty **then**
                End while
            next_node ← randomly choose an entity from $N_{current}$
            $edge\_weight$ ←transition score r from current_node to next_node
            $path\_probability = path\_probability \times edge\_weight$
            current_node ← next_node
            $path\_length = path\_length + 1$
        If current_node == $e_{depression}$ and $path\_length \leq p_{length}$ **then**
            $p_{trans} = max(p_{trans}, path\_probability)$
    Return p_{trans}

Appendix 4: Representative work of UGC for Depression Detection and Medical Knowledge Expansion

Table A4. Representative Work on Using UGC with Domain Knowledge for Depression Detection

References	Task/domain	Knowledge source/type & Knowledge's role	How knowledge is integrated	Learning method
(Chau et al., 2020)	Identifying emotionally distressed bloggers (Chinese)	- Expert-authored rules (domain knowledge) - Rules inject domain priors and improve utility/precision in high-risk retrieval	Hybrid design: combine machine learning classification with rule-based classification derived from experts	Traditional machine learning and system-level hybrid

(Yang et al., 2022)	Stress & depression detection from social posts	- Commonsense/mental-state knowledge from COMmonsEnse TransFormer - External commonsense makes latent mental-state reasoning more explicit for classification	Infuse knowledge via GRUs; knowledge-aware mentalisation (dot-product attention) to attend to relevant knowledge; supervised contrastive learning for class-specific features	Knowledge-aware RNN and attention with contrastive objective
(W. Zhang et al., 2024)	Depression detection from social-media traces	- Depression diagnosis-related entities (symptoms, life events, treatments) and depression ontology - Medical knowledge is operationalized as entities and an ontology that guide the final detector	Three modules: (1) NER extracts diagnosis-related entities (RoBERTa-based, transition/Stack-LSTM architecture); (2) construct/domain ontology; (3) knowledge-aware attention-based sequence model for detection	Pipeline and knowledge-aware detector (deep learning)
(D. Zhang et al., 2024)	Suicidal ideation detection from social media; generalization tests	- Suicidal ideation lexicon (domain terms) - Lexicon steers the Transformer's representation toward domain-salient cues; validated across languages/platforms	Model-level integration of a social-media suicidal ideation lexicon into a Transformer with aligned dynamic embeddings and lexicon-based enhancement capturing domain relevance + contextual importance	Knowledge-enhanced Transformer
(Zhong et al., 2019)	Emotion detection in conversations (social media settings)	- External commonsense (e.g., ConceptNet/affective knowledge) - Shows consistent gains from injecting commonsense for social text semantics	Context-aware affective graph attention to incorporate external knowledge into Transformer context modeling	Knowledge-enriched Transformer
(W. Liu et al., 2020)	General language understanding; widely used in social tasks	- Knowledge graph triples (e.g., domain knowledge graphs) - Provides a general recipe for structured-knowledge injection into PLMs used in social-text analytics	Inject knowledge graph triples as additional tokens with soft-position & visibility controls to fuse factual knowledge into BERT	Knowledge-enabled BERT

Note: UGC: User-generated content

Table A5. Representative Work on Using User-Generated Content to Extend Medical Knowledge

References	UGC source	Knowledge representation	Methods & how it complements medical knowledge
(Kallinikos & Tempini, 2014)	Patient self-reporting networks	Community-curated patient data	IS qualitative analysis; shows UGC as "medical facts" alongside expert data
(Lavertu & Altman, 2019)	Reddit (health subreddits)	Lexicon and embeddings	Word embeddings; expands drug vocabulary beyond ontologies
(Nikfarjam et al., 2015)	Health social media	ADR mentions	Conditional random fields and embeddings; extracts drug–ADR relations for pharmacovigilance
(Smith et al., 2018)	Twitter (adalimumab posts)	ADRs mapped to UMLS	Semi-automatic extraction and UMLS mapping; complements FAERS
(Sarker & Ge, 2021)	Reddit (/r/covidlonghaulers)	Symptom lexicon to ontology IDs	Lexicon matching; surfaces long-COVID symptom knowledge
(Welivita & Pu, 2022)	Reddit distress dialogues	UGC-derived KG (22k nodes, 104k edges)	Topic modeling and clustering; builds knowledge graph of stressors/affect
(Gao et al., 2025)	Literature + curated DBs	Multi-relational KG (MDKG)	LLM-assisted knowledge graph construction; expands mental-health knowledge

Note: UGC: User-generated content; ADR: Adverse Drug Reaction; UMLS: Unified Medical Language System; KG: Knowledge graph