Kathmandu University Journal of Science, Engineering and Technology, Vol. 18, No. 2, December 2024

Kathmandu University
Journal of Science, Engineering and Technology

Cognify: Enhancement of Mental Conditions Using Cognitive Tools

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Abstract

Mental health conditions such as anxiety, depression, and attention-deficit/hyperactivity disorder (ADHD) are increasingly prevalent, yet scientifically grounded and accessible tools for their management remain limited. This paper introduces Cognify, an integrative conceptual framework combining psychiatry, natural language processing (NLP), and cognitive science to provide a holistic approach to mental health support. The platform initiates with validated psychiatric assessments and continuously adapts through dynamic journal analysis and personalized cognitive interventions. Through sentiment analysis and cognitive task performance, Cognify delivers feedback-driven, evidence-based interventions. By bridging clinical psychiatry with NLP and cognitive tools, Cognify presents a scalable and personalized mental health support system suitable for both clinical and non-clinical contexts.

Keywords: Mental health; Natural language processing; Psychiatry; Cognitive science.

1. Introduction

Mental health disorders like Anxiety, Depression, and Attention-Deficit/Hyperactivity Disorder (ADHD) affect nearly one in eight people globally, with over 970 million individuals impacted as of 2019 [1]. These conditions can severely impair cognitive functioning, emotional regulation, and quality of life. The COVID-19 pandemic further intensified this crisis, contributing to a 25% global surge in mental health disorders [2]. Despite the growing burden, access to timely, personalized, and clinically grounded mental health support remains a challenge due to factors such as social stigma, shortage of professionals, and high treatment costs, particularly in developing nations.

Digital mental health interventions have gained traction in recent years, but their effectiveness is often hindered by a lack of personalization, scientific rigor, and long-term engagement strategies. Research in [3] and [4] indicates that while mobile health apps can reduce symptoms of mental illness, most lack dynamic adaptation to the user's psychological state. Simultaneously, prior research has shown that language use in written text reflects psychological states and mental health conditions. Pennebaker et al. analyzed linguistic markers such as pronoun use, emotional tone, and cognitive complexity, showing their relationship to emotional and cognitive well-being [5]. Building on this, Resnik et al. used supervised topic modeling on social media data to detect depression-related linguistic patterns in real-world contexts [6]. Despite these advances, few tools leverage such insights for ongoing, real-time intervention.

In response to these challenges, we introduce *Cognify*, an AI-driven mental health application that combines initial standardized psychological screening, dynamic journal analysis, and evidence-based cognitive training to offer adaptive, user-centered care. Upon registration, users complete validated psychological assessments—PHQ-9 (Patient Health Questionnaire-9) [16] for depression, GAD-7 (General Anxiety Disorder-7) [17] for anxiety, and ASRS (Adult ADHD Self-Report Scale) [7] for ADHD traits—to classify them into one of the supported mental health domains: anxiety, depression, or ADHD. Based on this classification, the app recommends targeted cognitive exercises, such as the Flanker Task [12], Stroop Task [13], or N-back Task [14], designed to improve attentional control, cognitive flexibility, and emotional regulation.

Beyond static screening, *Cognify* also incorporates a journaling feature that allows users to freely express their thoughts, experiences, and daily activities. These entries are processed using advanced NLP techniques to detect linguistic cues such as sentiment, emotional tone, and cognitive distortions. The extracted insights are then fed back into the recommendation system, refining the set of cognitive games and mindfulness activities provided to the user in a personalized and iterative manner. Through this integration of clinical screening tools, cognitive science-based interventions, and dynamic NLP feedback, *Cognify* aims to go beyond symptom tracking to actively enhance mental well-being. This paper presents the conceptual design, scientific grounding, and system architecture of *Cognify*, demonstrating its potential as a scalable and intelligent platform for personalized mental health support.

2. Related Work

NLP techniques have shown promise in mental health detection by analyzing linguistic patterns from user-generated text. Pennebaker et al. demonstrated that word usage reveals emotional states and psychological conditions [5]. Studies in [6], [9] applied topic modeling and supervised learning to detect depression-related content on social media. Tools like Linguistic Inquiry and Word Count (LIWC) and transformer-based models [4] have enhanced context-aware emotional detection.

Clinically validated instruments such as PHQ-9, GAD-7, and ASRS are commonly employed for screening depression, anxiety, and ADHD symptoms respectively. While many apps use them for ini-

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Table 1: Comparison of Digital Mental Health Platforms

Feature	Wysa	Woebot	Cognify
Initial Assessment	Uses standardized assessments for progress tracking	Mood/craving tracking. No initial clinical classification	Clinical screening (PHQ-9, GAD-7, ASRS) to classify users
Personaliz ation	Rule-based AI with tailored programs	Provides "tailored content" and empathy	Dynamic NLP analysis of journal entries continuously refines recommendations
Real-time Adaptation	Responds to user emotions and updates models	Offers "real-time support" for urges	Closed-loop feedback from journal analysis and task performance
Intervention	CBT/DBT-based chats, meditation, yoga	CBT lessons and tools	Targeted cognitive tasks (Flanker, Stroop, N-back) mapped to conditions
Unique Contribution	Immediate, accessible care via conversational AI	Reduces stigma through non-human chat interface	Integrates clinical screening, NLP and adaptive cognitive tasks in feedback loop

tial screening, few integrate results into adaptive interventions. While digital mental health platforms such as Woebot [10] and Wysa [11] have made significant strides in offering accessible self-help and CBT-based conversational support, their mechanisms for deep, continuous personalization and dynamic adaptation to evolving user needs and psychological states remain a recognized challenge in the field. Research indicates that many digital mental health apps struggle to dynamically adapt based on user behavior over time [3]. To clearly delineate Cognify's advancements in this regard, particularly its unique adaptive features and integrated approach, a structured comparison with these prominent tools is presented in Table 1.

Cognitive tasks like the Stroop, Flanker, and N-back are effective for improving attention and emotional regulation [15].Particularly, Flanker task taps on interference suppression [22] and Stroop task taps on inhibition of prepotent response [22, 23]. However, most systems use these in generic formats without tailoring to individual mental conditions. *Cognify* differentiates itself by integrating clinical screening, NLP-based journaling analysis, and adaptive cognitive games within a continuous feedback loop, an approach aligned with recent calls for active intervention over passive monitoring.

3. Methodology

Cognify is built as a personalized mental health platform combining clinical screening, cognitive interventions, and NLP-driven feedback. The methodology is structured around a continuous, user-centered feedback loop that begins with standardized assessments and evolves through adaptive task recommendations and journaling insights. Figure 1 illustrates the system workflow.

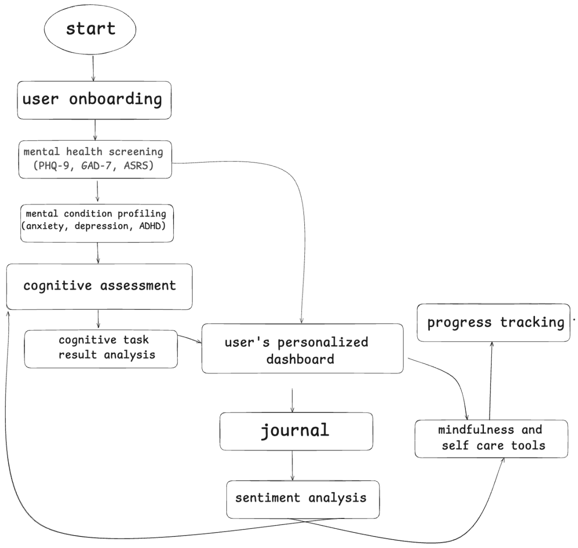

Figure 1: System workflow

Upon initial use, the user provides personal information, including age, gender, prior mental health history, and daily routine. Following this, they complete clinically validated self-assessment scales: PHQ-9 for depression [16], GAD-7 for anxiety [17], and ASRS for ADHD traits [7]. Based on the aggregate scores, the system classifies users into one of the target mental health conditions: anxiety, depression, or ADHD.

Once categorized, users are directed to condition-specific cognitive tasks, such as the Flanker Task, Stroop Task, or N-back Task, to target attention control, cognitive flexibility, and emotional regulation [15]. The performance results from these tasks populate a personalized dashboard, which visualizes progress and informs the next set of tasks. The system also includes a journal feature, where users can freely write about their emotions, experiences, and daily activities. These journal entries undergo sentiment and linguistic analysis using a hybrid BERT-CNN architecture [18], which combines contextual embeddings from BERT with the feature extraction power of convolutional neural networks to detect emotional tone, cognitive distortions, and temporal trends. The insights derived are used to refine both cognitive task recommendations and mindfulness exercises (e.g., guided breathing, attention redirection), making the intervention more adaptive.

3.1. Proposed Adaptive Task Selection Algorithm

The core innovation of Cognify's conceptual framework lies in its proposed adaptive task selection mechanism, which would dynamically adjust interventions based on real-time analysis of user journal entries and performance history. Algorithm 1 presents the proposed pseudocode for this adaptive process.

The proposed algorithm would operate in three distinct phases: **feature extraction**, **condition-specific mapping**, and **difficulty calibration**. In the feature extraction phase (lines 3-5), journal entries would be processed through the hybrid BERT-CNN architecture to extract sentiment polarity, emotional states, mental health indicators, and cognitive distortion patterns. The condition-specific mapping phase (lines 7-16) would apply evidence-based intervention protocols tailored to each mental health condition. For anxiety, the presence of anxiety markers would trigger attention-redirecting tasks (Flanker) combined with immediate relief interventions (breathing exercises). Depression-related negative sentiment patterns would activate cognitive stimulation tasks (N-back) alongside behavioral activation exercises. ADHD classifications would consistently receive working memory enhancement

Algorithm 1 Adaptive Task Selection

```
1: Input: Journal_Entry, User_Profile, History
2: Output: Personalized_Tasks
3: // Extract features using BERT-CNN
4: features ← NLP_Analysis(Journal_Entry)
5:     → sentiment, emotions, mh_indicators, distortions
6:
7: // Map to interventions based on condition
8: if User_Profile.condition == "anxiety" then
9:     if anxiety_markers in features then
10:        recommend: Flanker (attention), Breathing (relief)
11:    end if
12: else if User_Profile.condition == "depression" then
13:    if negative_sentiment in features then
14:        recommend: N-back (activation), Behavioral_tasks
15:    end if
16: else if User_Profile.condition == "adhd" then
17:    recommend: N-back (working memory), Attention_tasks
18: end if
19:
20: // Adaptive difficulty
21: for each recommended_task do
22:    adjust_difficulty_based_on(History.performance)
23: end for
24:
25: return calibrated_tasks
```

through N-back tasks and sustained attention training. Finally, the difficulty calibration phase (lines 18-20) would ensure optimal challenge levels by analyzing historical performance metrics and adjusting task parameters accordingly.

This proposed algorithmic approach would enable Cognify to move beyond static intervention delivery toward a truly personalized and responsive mental health support system. While the underlying NLP components have been preliminarily validated on public datasets (achieving an F1-score of 0.99 for mental health classification), the complete adaptive algorithm remains to be implemented and empirically validated. The intervention mappings are grounded in established cognitive science literature, providing theoretical foundation for future implementation.

Progress tracking is maintained throughout, based on both cognitive task performance and linguistic changes in journal entries. This creates a closed-loop feedback mechanism where the system continuously evolves its recommendations based on real-time emotional and cognitive indicators, enhancing both precision and engagement in mental health intervention.

3.2. Ethical Considerations

Cognify's design incorporates ethical safeguards to protect users and ensure responsible use of sensitive mental health data. Key considerations include:

- **Informed Consent:** Users will provide explicit consent, detailing data collection purposes and user rights, including the ability to withdraw at any time.
- **Data Privacy and Security:** The platform will use industry-standard encryption for data both in transit and at rest. The system will also adhere to privacy frameworks like GDPR and HIPAA to manage data access and retention.
- **Anonymization:** Personal identifiable information (PII) will be stored separately from journal and assessment data. The NLP pipelines will include automated PII removal.
- **Bias Mitigation:** The NLP models will be regularly audited for bias across different demographic groups. Training data will be curated to include diverse linguistic contexts, and Explainable AI (XAI) techniques will be used to ensure model decisions are interpretable.
- **Clinical Risk Management:** Cognify is a supplementary tool, not a replacement for professional care. The application will include disclaimers and implement automated alerts for severe distress or suicidal ideation, prompting referral to helplines or emergency services.

3.3. Proposed Adaptive Mechanism Examples

To illustrate how Algorithm 1 would operate in practice, the following hypothetical scenarios demonstrate the proposed journal analysis and intervention adaptation process:

Scenario 1 - Anxiety Detection:

- **Hypothetical Journal Entry:** *"Can't stop thinking about tomorrow's presentation. Heart racing, can't sleep."*
- **Proposed NLP Processing:** Text would be analyzed for anxiety indicators (racing thoughts, physical symptoms, sleep disruption)
- **Proposed System Response:** Algorithm would recommend increased attention-control tasks and immediate anxiety relief techniques

Scenario 2 - Depression Monitoring:

- **Hypothetical Journal Entry:** *"Everything feels pointless today. Stayed in bed until 2 PM. Don't see the point in trying."*
- **Proposed NLP Processing:** Analysis would detect negative sentiment, behavioral withdrawal, and hopelessness markers
- **Proposed System Response:** System would suggest gentle behavioral activation and mood-lifting cognitive tasks

Scenario 3 - ADHD Progress Tracking:

- **Hypothetical Journal Entry:** *"Used the timer technique and actually finished my assignment! Focus is getting better."*
- **Proposed NLP Processing:** Text would identify strategy adoption and positive reinforcement patterns
- **Proposed System Response:** Algorithm would maintain current difficulty levels and introduce advanced attention tasks

Note: These examples represent the proposed functionality of the Cognify framework. Implementation and empirical validation of these adaptive processes are planned for future development phases.

4. Results and Discussion

As this study is currently at a conceptual stage, the results are discussed in terms of system design feasibility and alignment with existing evidence. *Cognify* integrates standardized mental health screening tools (PHQ-9, GAD-7, ASRS) to categorize users into anxiety, depression, or ADHD. This triaging allows early, condition-specific cognitive interventions rooted in established psychological frameworks. For instance, the system maps ADHD classifications to working memory tasks like N-back, while anxiety cases receive attention-shifting exercises such as the Flanker or Stroop task-strategies supported by cognitive science literature [15].

The system's novelty lies in its journal-based NLP module, which performs sentiment and linguistic analysis on user-generated entries [4]. These insights inform real-time updates to recommended cognitive tasks and mindfulness activities, enabling a dynamic feedback loop. This approach responds to gaps in current digital mental health apps, which often lack personalization or continuous adaptation [4], [3]. Though not yet tested, the architecture demonstrates strong theoretical grounding and practical feasibility. *Cognify*'s modular structure enables future empirical evaluation and refinement. It represents a scalable, user-centered alternative to static mental health tools by combining psychiatry, NLP, and cognitive science into a unified, adaptive framework.

4.1. Preliminary NLP Module Evaluation

To validate the feasibility of Cognify's NLP module, a multi-task BERT-CNN model was implemented and trained on three publicly available datasets:

- **Reddit Mental Health Dataset:** Used for diagnostic screening of depression, anxiety, and ADHD [19].
- **GoEmotions:** Used for sentiment and emotion classification [20].
- **Cognitive Distortion Detection Dataset:** Used to classify 10 types of cognitive distortions [21].

The model's performance on validation sets, measured using macro-F1 scores, was as follows:

- **Sentiment:** 0.7357
- **Emotion (multi-label):** 0.3018
- **Cognitive Distortion:** 0.4783
- **Mental Health:** 0.9907

These preliminary results indicate strong performance in sentiment and mental health classification, validating the module's potential for integration within Cognify. The model showed moderate performance in detecting cognitive distortions and has room for improvement in multi-label emotion detection, likely due to label imbalance. Future work will focus on refining these modules through data augmentation and hyperparameter optimization.

5. Conclusion

This paper presented Cognify, a theoretically grounded mental health platform that integrates clinical screening tools, cognitive science-based interventions, and NLP-driven journal analysis to provide personalized mental health support. By combining validated assessment metrics (PHQ-9, GAD-7, ASRS) with adaptive cognitive tasks and real-time sentiment analysis, Cognify aims to deliver dynamic and user-centered interventions for individuals experiencing anxiety, depression, or ADHD. Unlike many existing mental health applications that rely on static content, Cognify introduces a feedback-driven architecture where emotional and cognitive inputs continuously inform task recommendations. This approach offers a scalable and customizable alternative to traditional interventions, bridging the gap between psychiatric assessment and interactive therapy.

Although still in its design phase, the system's conceptual framework demonstrates strong alignment with existing scientific literature and holds significant promise for future development. To move Cognify from a conceptual framework to a fully validated solution, our future work will focus on a multi-stage empirical evaluation.

Initially, small-scale user studies will be conducted to refine the platform's usability and user experience. This qualitative phase will involve a limited number of participants who will test the app's interface, navigability, and the clarity of cognitive tasks and journaling features. Feedback will be collected through interviews and surveys to identify and address any design flaws before a wider deployment. Our application will recruit linguistic [28, 30, 24] and cognitive mechanisms across different age groups including children [25, 26, 27].

Following this, the system will be evaluated through a Randomized Controlled Trial (RCT) to rigorously validate its clinical efficacy. A cohort of participants will be recruited and screened based on the supported mental health conditions: anxiety, depression, or ADHD. These participants will be randomly assigned to either an intervention group, which uses the full Cognify platform, or a control group. The control group will receive an alternative, non-adaptive intervention, such as a traditional digital journaling tool without the NLP analysis or a waitlist. The trial will run for a predefined period, likely 8-12 weeks, during which both groups will complete a baseline assessment and the primary outcome of the RCT will be the statistically significant change in symptom severity scores between the two groups (measured via PHQ-9, GAD-7, and ASRS), with secondary outcomes including changes in cognitive performance metrics from in-app tasks (e.g., improved reaction time and accuracy on Flanker, Stroop, and N-back tasks) and shifts in linguistic markers and emotional tone in journal entries analyzed by a hybrid BERT-CNN model.This application will validate the cognitive science driven mental health interventions [29, 31].

This rigorous approach will provide the empirical evidence needed to substantiate Cognify's effectiveness and establish it as a clinically meaningful mental health solution.

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