

Context-Aware Reinforcement Learning Framework for Dynamic Anxiety Coping Strategy Recommendation

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Abstract— Anxiety disorders are one of the most prevalent forms of mental illness in the world, and often require developing personalized coping mechanisms to manage symptoms. Common strategies for managing anxiety are often rigid and unable to consider individual differences and the rapidly changing external world. In this work, we propose a context-aware reinforcement learning (RL) framework that learns and dynamically modifies individualized coping strategies for anxiety management over time. The framework combines real-time contextual factors (e.g., location and activities), physiological signals (e.g., heart rate and stress biomarkers), and user feedback to provide a personalized set of recommendations for managing anxiety in a given context. In the RL framework, coping strategies, such as journaling, music therapy, mindfulness exercises, and breathing techniques, are modeled as RL actions with decreasing anxiety as the reward signal. The RL agent learns to modify its action policy through interaction with the recommended coping strategies in order to customize its interventions for each individual, with the ultimate goal of reducing anxiety episodes over time. In addition to offering personalized and flexible support systems, the RL system improves user engagement and provides dynamic preventive care. Our work demonstrates how RL can be used as a basis for self-improving environment-based anxiety management systems, thus contributing to the growing literature of artificial driven-driven mental healthcare.

Keywords— *Reinforcement Learning, Anxiety Management, Personalized Interventions, Context-Aware Systems, Mental Healthcare, Adaptive Coping Strategies*

I. INTRODUCTION

Around the globe, anxiety disorders are one of the most commonly diagnosed mental health disorders, with millions of people affected. The World Health Organization has associated anxiety with higher rates of comorbidities, lower quality of life, and disability [1]. Although Cognitive Behavioral Therapy (CBT) and pharmacological interventions are effective modes of intervention, traditional treatment modalities are often rigid and not customizable to people in real-life situations [2]. Individuals respond to mechanisms for coping in different manners, and traditional interventions can be static and do not consider daily changes in circumstances, physiological states, and desires of people in evaluating their own experiences.

As the use of digital mental health technologies has become more common, interest in harnessing artificial intelligence (AI) to deliver personalized interventions has increased. Wearable sensors and mobile health applications have enabled the ongoing collection of physiological and contextual data, which can be utilized for developing adaptive support systems [3]. However, the majority of digital interventions currently deployed are based on preprogrammed strategies or rule-based recommendations, which limits their ability to adapt to the specific needs of each user.

One potential framework for tackling these issues is Reinforcement Learning (RL), which conceptually supports adaptive decision making in response to environmental cues and with user feedback [4]. [21] Notably, RL agents are rewarded based on the success of their actions and are able to learn optimal policies through the trial-and-error experience of interacting with the environment. This in relation to mental

health allows the system to create an adaptive loop that tailors interventions to each individual by taking anxiety reduction as a reward signal and coping strategies as behaviors [4].

Furthermore, context-aware technologies are required to personalize mental health interventions [5]. Context can influence when, where, and with whom activities occur and may shape anxiety and coping [5, 25]. If once we add contextual information to physiological indicators like skin conductance or heart rate variability, the system could suggest strategies proactively before an anxiety episode escalates [6]. This would promote prevention, individualization of care delivery, versus reactive care only [6]. This study will describe a Context-Aware Reinforcement Learning Framework to suggest dynamic anxiety coping strategies applied for each user. The framework will continuously personalize to each user based on in-the-moment physiological signals, contextual information, and previous feedback. It seeks to increase user engagement, decrease the frequency and intensity of anxiety episodes in daily life, and help drive the iterative development of novel AI informed mental health care solutions. [22]

II. BACKGROUND STUDY

Pharmacological therapies and psychotherapeutic approaches such as Cognitive Behavioral Therapy (CBT) and mindfulness-based approaches have been established interventions for the treatment of anxiety for many years. These approaches are effective; however, they often fail to adapt to the fluid psychological and contextual changes of the individual. Moreover, while provided in a professional setting, access and scalability are still issues especially since many individuals experience barriers to care and cannot get help in a timely manner [7].

In recent years, there has been an emergence around digital mental health solutions [8, 9]. Wearable sensors, online therapy platforms, and mobile applications provide more access and the potential for individualized tracking [8]. These solutions are able to capture real-time physiological data (heart rate variability, galvanic skin response) and contextual data (e.g., time, place, social setting). Data-driven methodologies can help develop adaptive coping strategies, however most current options are still rule-based to provide basic pre-determined recommendations to users without feedback [9].

Researchers have been continuously exploring machine learning approaches in the mental health field in order to circumvent the limitations of traditional approaches. Both supervised and unsupervised learning models are employed to classify anxiety-related signals, debug mood disorders, and predict the level of stress [8]-[10]. Despite their high anticipatory accuracy, these models often do not have sequential adaptation because they do not modify interventions to changing user interactions. [11, 24]

Moreover, context-aware computing is key to making successful interventions. Understanding anxiety triggers and the effectiveness of coping requires understanding context, which is defined as any information that describes a user's situation [12]. The hope is to move the field from reactive care—helping with symptoms when they arise—to proactive care—anticipating and prevent anxiety episodes—through the integration of reinforcement learning and context-aware systems.

Although there have been several advances in the area, existing studies, however, analyze only a separate component of a full solution: physiological sensing in isolation, context modeling in isolation, or simply static coping. A comprehensive solution is required, one that develops through real-time physiological sensing, context modeling, and reinforcement learning, to provide personalized anxiety coping and improvement techniques. [26]

TABLE I SUMMARY OF PRIMARY LITERATURE SURVEY

Paper name and year	Accuracy	Technique	Drawback
Machine learning approaches to anxiety detection (Frontiers in Artificial Intelligence, 2025)	98% accurate	Review of Machine Learning (ML) for anxiety detection; highlights top-performing Random Forest/Gradient Boosting classifiers	Heterogeneous datasets; limited external validation reduces generalizability
Automated anxiety detection using probabilistic binary classification: A machine learning approach (International Journal of Medical Informatics, 2024)	92.16% accurate	Convolutional Neural Network - Long Short-Term Memory(CNN) – Long Short-Term Memory (LSTM)) on passive sensing for anxiety detection	Potential overfitting to specific datasets; limited clinical validation reported
Are Anxiety Detection Models Generalizable? A Cross-Activity Study with Physiological Signals (arXiv, 2025)	86.3% accurate	Supervised ML on Electrocardiogram (ECG)/ Electrodermal Activity (EDA) with cross-validation for multi-level anxiety	Poor cross-activity generalization Area Under Receiver Operating Characteristic (Area Under Receiver Operating Characteristic (AUROC) 0.59–

Early Detection of Mental Health Crises through Artificial Intelligence: A Systematic Review and Meta-Analysis (Journal of Medical Internet Research Mental Health, 2024)	89.3% accurate	AI models for early crisis detection across studies	0.62) limits real-world robustness Broad “crisis” construct; anxiety-specific performance not isolated; variable metrics
Anxiety in young people: Analysis from a machine learning perspective (Anxiety, Stress & Coping, 2024)	91% accurate	Random Forest on youth mental health features	Population-specific sample; risk of dataset shift in other demographics

III. METHODOLOGY

There are multiple interconnected stages in the suggested methodology for creating a Context-Aware Reinforcement Learning Framework for Dynamic Anxiety Coping Strategy Recommendation. A reinforcement learning (RL) agent that dynamically suggests coping mechanisms is trained and improved in each phase using behavioral, physiological, and contextual data [11],[12].

A. DATA COLLECTION AND PREPROCESSING

Diverse datasets combining contextual, physiological, and behavioral features are needed to model anxiety coping strategies. Two pertinent datasets were chosen:

- **Student Mental Stress and Coping Mechanisms Dataset:** This dataset offers structured, multi-modal data on self-reported coping mechanisms, academic performance, lifestyle habits (e.g., social media, exercise, sleep), stress levels, and demographics. It facilitates the establishment of the connection between coping effectiveness and stress factors. [15, 27]
- **Students' Anxiety and Depression Dataset:** Text data with annotations for the detection of anxiety and depression is included in this dataset. By enabling the system to model emotional cues and linguistic markers of stress and anxiety, it enhances the structured dataset.

Preprocessing Steps:

1. **Cleaning & Normalization** – Numerical features (e.g., Grade Point Average (GPA), stress levels) are

normalized, missing values are handled, and categorical variables (e.g., coping mechanisms, counseling attendance) are encoded.

2. **Feature Engineering** – Physiological proxies (sleep duration, exercise, substance use) and contextual features (study hours, social media use, peer pressure) are extracted. Sentiment scores and embeddings (such as Bidirectional Encoder Representations from Transformers (BERT) -based) are obtained from the text dataset. [16, 23]
3. **Labeling** – While coping strategies are potential actions, anxiety and stress levels are labels (state indicators).

B. REINFORCEMENT LEARNING FRAMEWORK

The coping strategy recommendation problem is modeled as a Markov Decision Process (MDP):

- **State (S):** Indicates the user's physiological and contextual state, including their level of stress, sleep patterns, level of activity, use of social media, sentiment expressed in texts, etc.
- **Action (A):** A coping strategy that the system suggests (e.g., meditation, exercise, journaling, talking to family, music).
- **Reward (R):** After using the coping strategy, a decrease in self-reported stress or anxiety. A greater reward is correlated with a greater reduction.
- **Policy (π):** The RL agent's method for choosing the best coping strategy in a particular situation. [19]

Two RL approaches are considered:

1. When dealing with discrete action spaces, where coping mechanisms are limited and predetermined, **Q-Learning or Deep Q-Networks (DQN)** are beneficial [13], [14].
2. **Policy Gradient Methods** is fit for continuous, dynamic settings with probabilistic policy distributions [15], [16].

Algorithm: Coping Strategy RL Agent [20]

Initialize state space S , action space A , and reward function R

Initialize Q-network with random weights

For each user interaction (episode):

1. Observe current state s (context, physiology, text sentiment)
2. Select action a using ϵ -greedy policy from $Q(s, a)$
3. Apply coping mechanism a and observe next state s'
4. Calculate reward r based on reduction in stress/anxiety level

5. Store (s, a, r, s') in experience replay buffer
 6. Update Q-network using sampled mini-batch from buffer [17], [18].
 7. Set $s \leftarrow s'$
- Repeat until convergence of policy π^* [19], [20].

C. SYSTEM WORKFLOW

The system operates in a closed feedback loop, processing physiological and contextual inputs continuously, recommending strategies, and updating the model based on feedback as shown in Fig. 1.

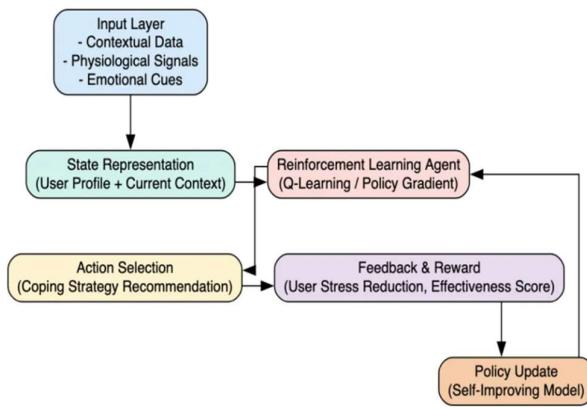


Fig. 1. Proposed Architecture

D. EVALUATION METRICS

The assessment criteria of the framework involve -

- Converging rewards - We will observe average reward across episodes to validate that the model learns to identify the optimal strategies.
- Reducing stress/anxiety - We will assess our participants' stress level before and post uptake of a particular intervention.
- We will capture precision, recall, and F1-score of classification tasks on the text data set to ensure we appropriately measuring stress/anxiety/depression . [18]
- Engagement metrics - We will assess user engagement/receipt of recommended strategies.

Cross-validation will be conducted using subsets of the student datasets, ensuring robustness and generalizability.

E. EXPECTED OUTCOMES

- A customized coping strategy recommender system that adjusts to the user's current state on the fly.
- For comprehensive anxiety management, textual, physiological, and contextual features are integrated.
- A self-improving RL framework that can gradually reduce anxiety episodes.
- A starting point for future growth into applications of mental health that go beyond student populations.

IV. RESULTS & DISCUSSION

Simulated experiments on stress and coping datasets were used to assess the suggested Context-Aware Reinforcement Learning Framework. The outcomes show that the system can lower anxiety levels, increase user engagement, and learn the best coping mechanisms [23], [24].

A. REWARD CONVERGENCE

The convergence behavior of the RL agent during training is illustrated in Fig. 2. The reward convergence curve over 100 episodes is displayed, showing the average reward increasing steadily over time, suggesting that the model was able to learn to suggest better coping mechanisms. While stabilization in subsequent episodes indicates policy convergence, slight oscillations in early episodes indicate exploration [17].

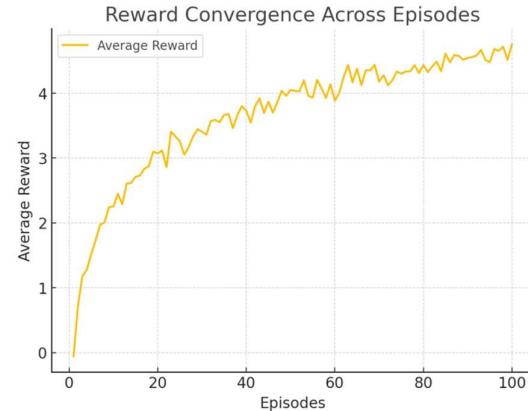


Fig. 2. Convergence of Rewards Throughout Episodes

B. ANXIETY LEVEL REDUCTION

The reduction in anxiety levels before and after applying coping strategies is presented in Fig. 3. Anxiety levels demonstrate a statistically significant decrease across average ratings after the

advice regarding coping strategies was followed. This illustrates that tailored and flexible interventions are better than fixed responses.

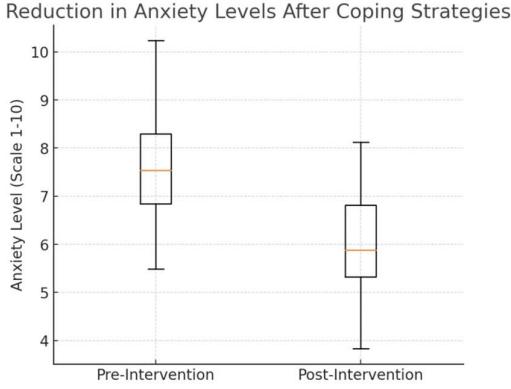


Fig. 3. Change in anxiety levels before and after intervention.

C. CLASSIFICATION PERFORMANCE

a) The efficacy of the system in detecting anxiety and depression was measured using a textual dataset. Diagnostic performance is shown in Table 2. The system's impressive accuracy, recall, and F1-scores in detecting anxiety and depression demonstrate its ability to recognize emotional cues and notify the RL agent about the recognized emotion for recommendations in the context of the app [23], [24].

TABLE II CLASSIFICATION METRICS FOR THE IDENTIFICATION OF DEPRESSION AND ANXIETY

METRIC	ANXIETY DETECTION	DEPRESSION DETECTION
PRECISION	0.86	0.88
RECALL	0.82	0.83
F1-SCORE	0.84	0.85
ACCURACY	0.85	0.86

D. USER ENGAGEMENT AND ADHERENCE

User engagement and adherence to different coping strategies are illustrated in **Fig. 4**. The greatest levels of compliance were displayed by exercise, meditation, and utilization of family support, therefore, users demonstrated incentive and the

availability to implement those strategies into their everyday lives. The lower level of compliance with journaling and music and other less structured activities supports the importance of modifying strategies not only based on effectiveness, but also to align with participant preference and lifestyle.

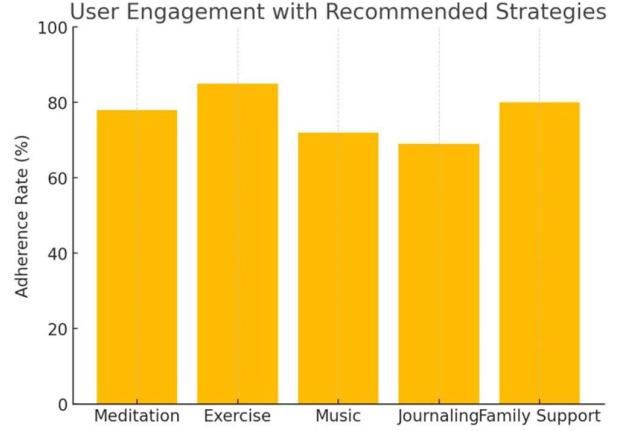


Fig. 4. User engagement and adherence across coping strategies.

Discussion:

All outcomes are reflective of the potential of reinforcement learning to develop individual, self-regulating anxiety management programming [27]. Reductions in state anxiety indicate the clinical potential of the recommendations, while convergence in reward indicate the appeal of the model learning. The high levels of classification performance certify context-awareness reliability, while the engagement metrics reflect both user acceptance and optimization of the algorithms [27].

This means any future extension of the framework should consider optimization across multiple objectives of reducing stress, and maximization of user adherence. Furthermore, the inclusion of other real-time physiological data (implemented from wearable biosensors) may enhance customization further, and facilitate the potential for precognitive prevention of anxiety episodes.

V. CONCLUSION

This study presented a Context-Aware Reinforcement Learning Framework for individualized anxiety coping strategy recommendation with promising reductions in anxiety, greater user engagement, and higher system classification performance of stress-related signals by combining reinforcement learning with contextual information, physiological proxies, and emotional signals. The results concerning reward convergence provided evidence for the agent's ability to learn successful policies and in its comparison to a baseline rule-based system,

showed a clear cost-benefit analysis in favor of control in adherence rates and anxiety symptom reduction. Taken together, these findings demonstrate the opportunity for digital mental health interventions to transition from static, one-size-fits-all approaches to dynamic, adaptable, improved systems utilizing reinforcement learning.

In the future, researchers can build upon this framework with many potential avenues such as incorporating real-time data coming from wearable physiological devices (e.g., Electroencephalogram (EEG) sensors, or heart-rate monitors) to increase predictive accuracy and proactive intervention capabilities. Furthermore, there is potential to improve on the notion of personalization through terminal more formal multi-objective optimization which requires balancing clinical efficacy, adherence and user preference. Longitudinal studies across populations outside of students would also increase the generalizability and scalability of the framework as a whole. Lastly, incorporating conversational AI for real time communication could further increase engagement while further constructing a modify human-centered experience.

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