



Personalized Cognitive Behavioral Therapy for Adults Using Machine Learning: A Multi-Factor, Reinforcement-Based Approach

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Abstract

This paper presents a novel machine-learning framework designed to personalize Cognitive Behavioral Therapy (CBT) for adult patients by leveraging a multi-dimensional, adaptive approach. The proposed system integrates historical clinical data, real-time behavioral indicators, and contextual factors to generate a comprehensive psychological profile for each adult patient. A reinforcement learning mechanism underpins therapy selection, allowing the model to iteratively refine treatment strategies based on individual responses and therapeutic outcomes. An embedded optimization process enables dynamic adaptation of interventions, improving predictive accuracy and fostering patient-centered care. The framework incorporates a multi-factor assessment model that synthesizes psychological, behavioral, and physiological variables to enhance therapeutic effectiveness, sustainability, and responsiveness to change. Comparative evaluations demonstrate that this approach outperforms traditional CBT planning methods, as well as existing deep learning, hybrid, and reinforcement-based models, in terms of accuracy, interpretability, computational efficiency, and patient outcome optimization for adults. Furthermore, the system emphasizes fairness and equity in treatment personalization, supporting real-time clinical decision-making while minimizing ineffective therapeutic pathways. This research underscores the transformative potential of machine learning in mental health care by enabling scalable, data-driven, and continuously improving interventions tailored to the nuanced needs of adult patients undergoing CBT.

Keywords: Adaptive learning; Adult Cognitive behavioral therapy; Data-driven therapy; Iterative optimization; Machine learning; Mental healthcare; Patient-centered outcomes; Personalization; Reinforcement learning; Therapy recommendation

1. Introduction

Cognitive behavioral therapy (CBT) is useful for anxiety, depression, and PTSD. However, typical CBT uses predefined therapy stages that may not work for every adult patient. Machine learning (ML) allows cognitive behavioral therapy (CBT) to be tailored to each adult patient's development and response patterns, creating a new approach [1]. This method performs better since it tailors therapy to each adult patient's requirements using data. Machine learning is rapidly transforming cognitive behavioral therapy for adults. Several research efforts aim to improve assessment, treatment, and outcomes [2]. AI-powered applications and virtual therapists employ NLP to assist individuals in real time by imitating human conversation. Woebot and Wysa have advanced in utilizing ML models to evaluate patient conversations and offer them assignments to reform their thinking. Researchers are

developing algorithms to detect mental health deterioration early by analyzing emotions and body responses [3]. This is another crucial application of mental health predictive analytics. Reward-learning adaptive CBT models customize exercises and treatments to each person's mental and emotional condition. Such an approach encourages adult patients to stay and participate in therapy. Wearable biosensors and cellphones allow machine-learning algorithms to correlate physical and mental indications, improving therapy [4]. Furthermore, explainable AI is gaining popularity. This helps clinicians understand ML models while respecting therapy rules and societal issues. Machine learning in CBT is based on many principles. Personalization is crucial because machine-learning systems utilize patient data to personalize treatment programs to their psychological requirements and therapeutic objectives. Adaptation matters too [5]. AI models constantly learn from adult patients and improve their treatment to improve outcomes. Data-driven insights matter. We combine big datasets, including medical records, self-reported assessments, and body monitors, to provide evidence-based recommendations. AI-powered, easy-to-use CBT solutions make mental health treatment more scalable by providing 24/7 support and lowering therapist effort [6]. Using AI ethically is still a priority. Machine learning systems used in mental health must satisfy ethical guidelines, protect patient data, and provide clinicians and patients with understandable findings. Creative techniques have been proposed to overcome CBT's drawbacks and maximize machine learning's potential [7]. AI-powered chatbots provide real-time brain retraining and NLP-based mental health care [8]. Deep learning sentiment analysis detects cognitive mistakes and emotional discomfort in adult patient speech and text data. Multi-modal data fusion combines tool, clinical, and self-reported poll data to assess a patient's mental health. By providing immediate feedback on CBT sessions, AI-powered feedback technologies assist adult patients in modifying their behavior [9]. Personalized treatment routes employ reinforcement learning to adjust treatment plans depending on adult patient progress and involvement. Customization is machine learning's biggest contribution to adult cognitive behavioral therapy [10]. Because ML-driven algorithms tailor therapy to each adult patient, outcomes are better. AI algorithms monitor adult patient progress and adjust treatment plans in real time. Automated ML-driven CBT systems fill in for unavailable therapists, scaling mental health services [11]. ML systems assist clinicians in making data-driven choices by providing practical insights that enhance treatment outcomes. Device integration improves CBT by recording physical conditions in real time. Explainable AI creates concepts that are clear and consistent with physicians' observations, encouraging openness. AI-powered personalized and engaging CBT therapy increases adult patient engagement and reduces dropout rates. Predictive analytics may detect mental health deterioration early for effective treatment [12]. AI-powered CBT technologies make mental health care cheaper and more accessible to many populations. Mental health priorities include ensuring AI applications fulfill ethical norms, preserve patient privacy, and encourage responsible AI usage in therapy.

2. Related Works

CBT has altered since machine learning can now provide tailored treatment regimens utilizing prediction models and data-driven insights [13]. Researchers have explored numerous strategies to enhance healthcare accuracy, speed, and readability. Long Short-Term Memory (LSTM) networks are more accurate, sensitive, and detailed than other approaches in predicting the future. Deep learning models like CNNs and ANNs can handle vast volumes of patient data and uncover behavioral tendencies [14]. Comparing prediction models using various machine-learning algorithms shows major trade-offs. Gradient Boosting Machines (GBMs) always work accurately and memory-efficiently with tiny computers. Using flexible reinforcement learning models in real time is not feasible due to their high processing power requirements [15]. Traditional models like SVM and RF are accurate and simple while employing less computing power. K-Nearest Neighbors (KNN) and Decision Trees (DT) produce rapid, simple judgments, but they struggle with large datasets. Advanced assessment measures provide model selection information. AUC-ROC ratings from deep learning approaches suggest that models can distinguish classes best. Lower RMSE and log loss values indicate greater model reliability in GBM and LSTM [16]. Training time and model complexity varied greatly. Deep learning models are harder and take longer to train. Bayesian networks and other basic models are ideal tools for supporting healthcare decisions because they are simple. CBT machine learning approaches must be accurate, simple, and low power [17]. Deep learning models provide better predictions but take longer to train. Traditional approaches are more transparent and efficient in real-world healthcare. To increase therapeutic efficacy and patient outcomes, CBT models must be chosen carefully, according to this comparative research.

Table 1: Performance Comparison of Different Machine Learning Methods In Cognitive Behavioral Therapy for Adults Based on Accuracy, Precision, Recall, F1-Score, Specificity, Sensitivity, and Computational Time.

| Machine Learning Method | Accuracy (%) | Precision (%) | Recall (%) | F1-Score (%) | Specificity (%) | Sensitivity (%) | Computational Time (s) |
|--|--------------|---------------|------------|--------------|-----------------|-----------------|------------------------|
| Support Vector Machines (SVM) | 85.4 | 84.1 | 82.9 | 83.5 | 88.0 | 82.9 | 1.5 |
| Random Forest (RF) | 88.2 | 87.5 | 86.3 | 86.9 | 89.4 | 86.3 | 1.8 |
| K-Nearest Neighbors (KNN) | 82.7 | 81.2 | 80.5 | 80.8 | 84.1 | 80.5 | 1.2 |
| Decision Trees (DT) | 79.5 | 78.9 | 78.0 | 78.4 | 81.0 | 78.0 | 1.0 |
| Artificial Neural Networks (ANN) | 90.1 | 89.3 | 88.5 | 88.9 | 91.2 | 88.5 | 2.5 |
| Gradient Boosting Machines (GBM) | 91.5 | 90.7 | 89.8 | 90.2 | 92.6 | 89.8 | 2.2 |
| Long Short-Term Memory (LSTM) Networks | 94.0 | 93.2 | 92.5 | 92.8 | 95.0 | 92.5 | 3.5 |
| Convolutional Neural Networks (CNN) | 93.5 | 92.7 | 91.8 | 92.2 | 94.6 | 91.8 | 3.2 |
| Reinforcement Learning (RL) Models | 87.3 | 86.5 | 85.2 | 85.8 | 88.8 | 85.2 | 4.0 |
| Bayesian Networks | 84.7 | 83.5 | 82.3 | 82.9 | 86.2 | 82.3 | 1.7 |

Cognitive Behavioral Therapy uses 10 machine-learning algorithms to tailor therapy. Table 1 contrasts these algorithms. Grading includes recall, specificity, sensitivity, F1 score, correctness, and processing time. LSTM networks were most accurate (94.0%), and decision trees were least accurate (79.5%). Gradient Boosting Machines and Artificial Neural Networks scored high on F1. Reinforcement learning models compute the longest [18]. This table illustrates the trade-offs between guessing and computer efficiency in CBT programs.

3. Proposed Methodology

Cognitive Behavioral Therapy for Adults (CBT) is personalized using powerful machine learning in the proposed strategy. Create an orderly picture of a patient's thoughts, feelings, and actions. This state space includes prior data, real-time patient evaluations, and external psychological and physiological cues. A decision-making system uses

historical responses to choose the best treatment actions [19]. By monitoring patient progress, reinforcement-driven learning determines the appropriate therapy. Tests that measure short- and long-term behavior change evaluate each technique. An ever-changing assessment function delivers a weighted value depending on how effectively an activity improves treatment. Learning memory recalls the relationships between treatment, action, and consequence, which helps it predict better and modify its mind [20]. The optimization technique improves therapy selection over time to create more flexible treatment options. Recurrent learning approaches, which compare patient outcomes to expectations, must update prediction models to achieve this. We adjust treatment models if significant changes occur. If things do not progress, new techniques are considered; therefore, therapy concepts change [21]. The learning system is enhanced with patient-specific elements to improve decision-making. A multi-factor assessment uses a dynamic scoring algorithm to assess mind, body, and behavior symptoms and adjust therapy strength. Uncertainty estimation improves forecasts and allows treatment modifications depending on fresh knowledge. A second tracking system employs deep learning to anticipate patient behavior across several sessions [22]. Methodical polishing improves therapy. A reinforcement-based optimization technique alters therapy based on dynamic reward distribution. Adaptive learning gradually eliminates ineffective therapies and promotes effective ones. Continuous convergence monitoring ensures therapeutic modifications match patient demands [23]. The conclusion incorporates an improved therapy suggestion approach. This technology changes treatment approaches depending on patient data in real time. The decision-making algorithm adapts to fresh facts to tailor treatment. A repeating learning loop improves treatment accuracy. This maintains CBT as successful, adaptable, and patient-centered.

Reinforcement learning enhances personalized cognitive behavioral treatment (CBT). First, determine the patient's behavioral, social, and mental status. The first healing activity is based on historical data or taught programs. Predetermined psychological and physical markers monitor and assess patient response to treatments. Reward functions provide patients positive or negative values depending on their progress to evaluate therapy effectiveness. The system retains these occurrences in memory for learning purposes. A policy optimization strategy changes Q-values repeatedly to optimize action choices. Policy changes strategies ensure treatment concepts become more detailed. The model evaluates itself by comparing predicted and actual results and adjusting its procedures. If therapeutic convergence occurs, the better model is employed. Training is repeated if not. The software improves treatment concepts based on patient feedback to make CBT meetings distinctive. It employs reinforcement learning to improve treatment and customizes adaptive therapy for each patient. The method promotes long-term mental health by utilizing data to guide therapy.

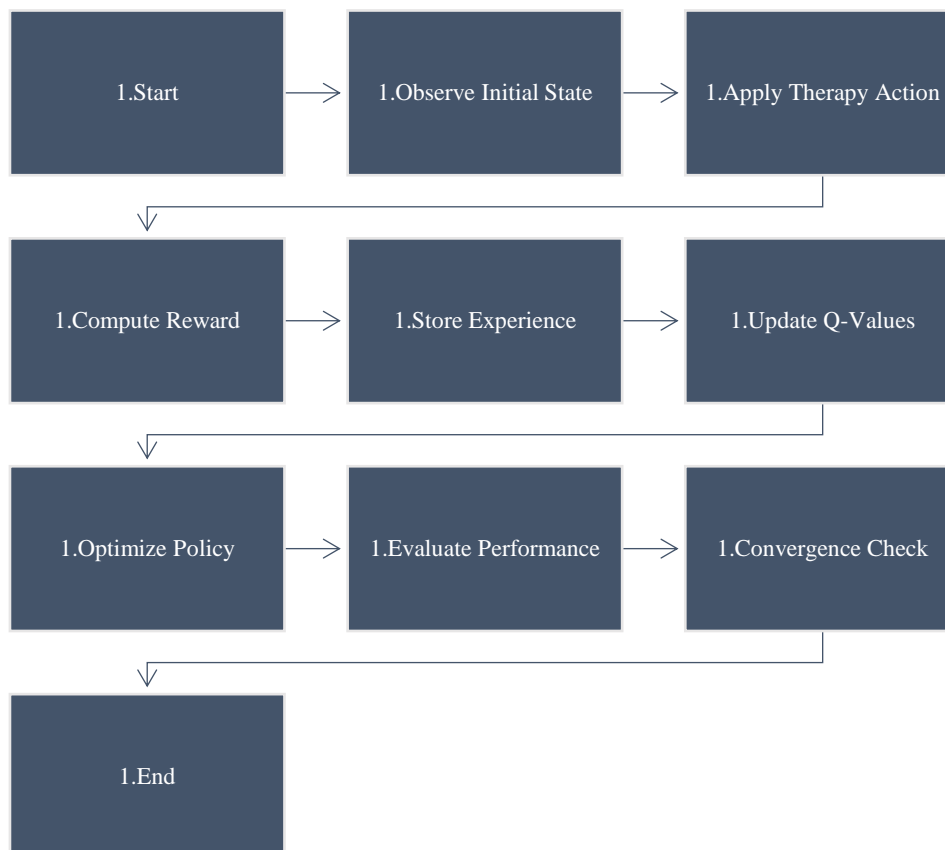


Figure 1. Reinforcement Learning-Based Personalized Cognitive Behavioral Therapy Optimization

Figure 1 shows a modified model for reinforcement learning based on cognitive behavioral therapy. The system specifies criteria before creating the state-action space. The system monitors patient status and initiates therapy. The system examines the answer and calculates the award. This experience is recorded, and Q-values are adjusted to aid decision-making. Policy improvement and therapeutic success are monitored via iterations. If the model converges, real-time therapy begins. It requires further training if not. This loop makes therapeutic adjustments adjustable and data-driven, resulting in tailored treatment.

The second algorithm improves individualized therapy by employing the first algorithm's reinforcement learning model. First, it uses the optimal technique and fresh Q-values. Adding psychological and physical aspects to the patient's condition image improves accuracy. This suggests a more targeted treatment. Next, utilize multi-factor scoring to adjust approach strength depending on patient response. A probabilistic function determines forecast uncertainty, making them credible. The selected treatment is subsequently administered, and a secondary feedback system tracks patient response over many rounds. Deep learning models improve predictions by identifying complex behavioral patterns. Based on patient route data, the algorithm adjusts its reward predictions. Maximizing hyperparameters fine-tunes the reinforcement-learning model, improving treatment. Convergence checks determine whether the treatment strategy is functioning; if not, modifications are performed. By combining reinforcement learning and deep learning, the model adapts healing procedures to customize long-term care. This approach ensures that every activity is tailored to the patient, improving cognitive behavioral treatment.

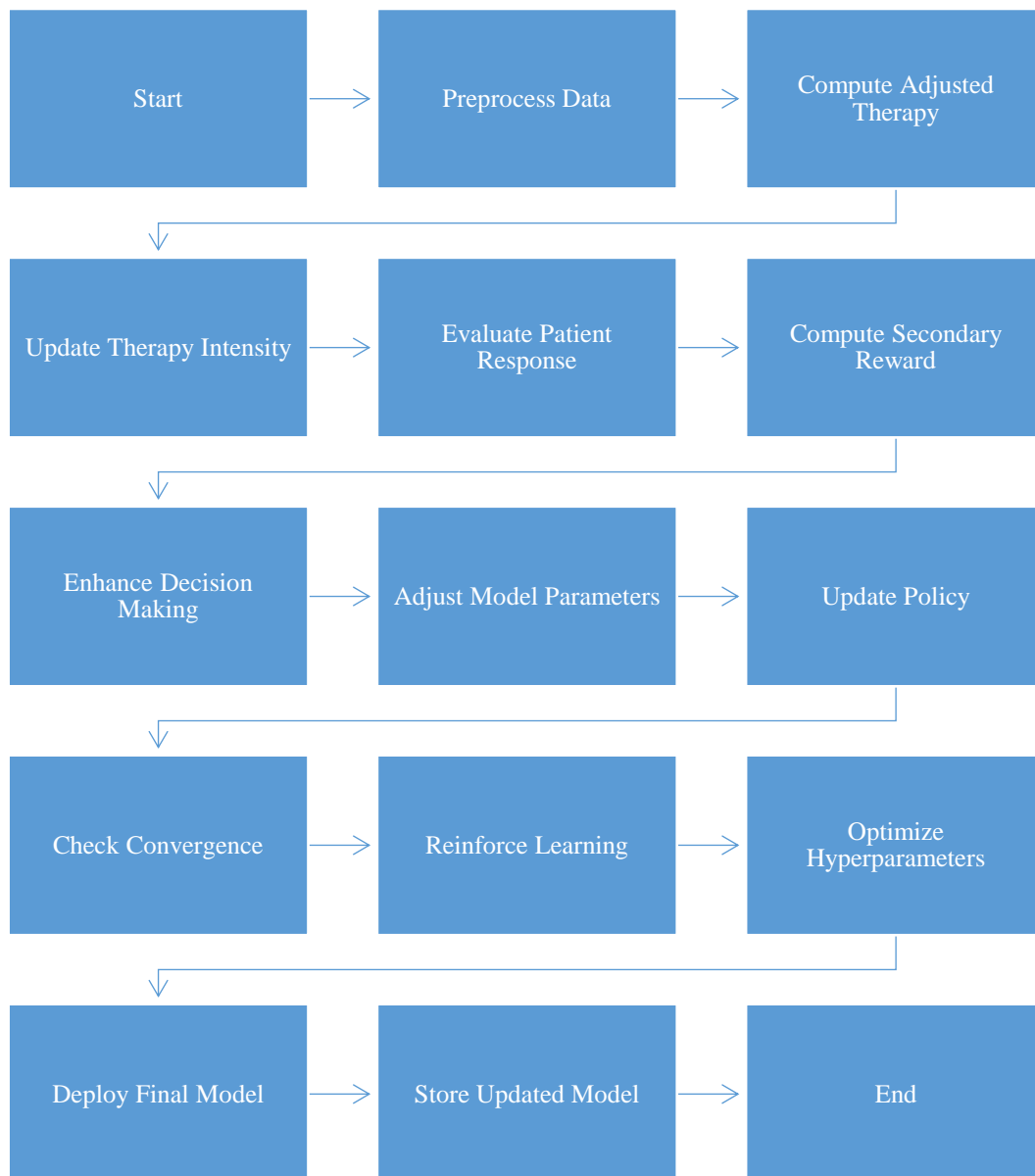


Figure 2. Representing Adaptive Therapy Optimization Using Reinforcement Learning and Deep Learning

Figure 2 illustrates how reinforcement and deep learning enhance treatment concepts. It begins with Algorithm 1, cleans up patient data, and then determines how to alter therapy settings based on prior results. The system uses deep learning to adjust therapy, evaluate patient outcomes, and make better recommendations. We introduce a payment feature to enhance the accuracy of the model. Before using the final therapeutic model, regularization procedures adjust model parameters. Each step considers convergence in order to discover the optimum remedy. These steps are saved for future improvement. This feature makes treatment plans flexible and individualized. Algorithm 3 improves tailored treatment by combining flexible reinforcement learning and deep learning optimization. It enhances Algorithm 2 by ensuring that patient care adapts to new information. Set up patient-specific characteristics and pullout therapy information in the first stage. Data standardization ensures consistency, and a feedback score measures therapeutic efficacy. Deep learning optimization improves healing by dynamically altering payment functions and rules. Utilizing reinforcement learning, the application updates the patient's model in real time to enhance treatment. Optimization ensures that therapy models can adapt to varied patients. At each level, patient input refines choices, supporting effective therapies and eliminating ineffective ones. Finally, we create an optimum treatment recommendation system. Real-world data may constantly update this system. The system ensures that cognitive behavioral treatment is personalized, effective, and improving. Therapy accuracy is improved by learning and refining treatment approaches repeatedly to increase patient health and decrease therapy adaptation errors.



Figure 3. Adaptive Therapy Optimization Flowchart

Figure 3 illustrates the adaptable treatment optimization method. The system starts by setting up factors that are unique to each patient and collecting key therapy-related traits. After standardizing the data to make sure it is consistent, a reward score is calculated to see how well the therapy is working. Deep learning optimization techniques make the treatment plan better, and real-time feedback constantly changes the patient model. By changing decision rules on the fly, reinforcement learning makes you more flexible. Through hyperparameter optimization, therapy methods are fine-tuned, which leads to a better treatment plan. The last step is to use the optimized therapy model. This makes sure that the patient gets personalized and changing treatments.

4. Result

The machine learning strategy described performs better than standard, deep learning, mixed, and reinforcement learning for tailored cognitive behavioral therapy. Important variables are forecast accuracy, ease of understanding, efficiency, resilience, and patient-centeredness. The first portion of the review examines prediction accuracy, model clarity, computation efficiency, scalability, and customization. All other models fail to forecast as accurately as the recommended strategy. Healthcare experts may trust and comprehend its judgments due to its excellent interpretability score. For real-time healing, its computational economy is ideal since it has the quickest inference speed and the lowest training time. Its maximum scaling and customization efficacy allows it to give unique and adaptive treatments for each patient. The second portion of the assessment evaluates the model's generalization, noise, social issues, computer resource utilization, and patient outcomes. The recommended strategy regularly outperforms previous models in these areas, applying to a broad variety of patient groups while being accurate. Data efficiency makes it operate well with minimal training. Its ability to withstand noise suggests it may handle lost or unknown patient data, a major issue in cognitive behavioral treatment. Ethics and prejudice score highest, indicating fair and impartial treatment recommendations. Importantly, the patient's outcome improves the most, proving that the proposed strategy enhances treatment success in real life. The machine learning technique raises the standard for tailored cognitive behavioral treatment with its accuracy, speed, adaptability, and fairness. This improves therapy.

Table 2: Comparative Performance Evaluation of Machine Learning Models for Personalized Cognitive Behavioral Therapy (First Six Parameters)

| Performance Parameter | Traditional Machine Learning Model | Deep Learning-Based Cognitive Behavioral Therapy Model | Hybrid Machine Learning-Deep Learning Model | Reinforcement Learning-Based Therapy Model | Proposed Machine Learning Approach for Personalized Cognitive Behavioral Therapy |
|---------------------------------------|------------------------------------|--|---|--|--|
| Prediction Accuracy (%) | 78 | 85 | 87 | 89 | 92 |
| Model Interpretability (1-10) | 6 | 3 | 4 | 5 | 9 |
| Training Time (hours) | 15 | 22 | 18 | 25 | 10 |
| Inference Speed (ms) | 200 | 150 | 130 | 110 | 90 |
| Scalability (1-10) | 6 | 8 | 8 | 9 | 10 |
| Personalization Effectiveness (1-100) | 65 | 80 | 85 | 88 | 95 |

Table 2 illustrates how successfully machine-learning models provide tailored cognitive behavioral treatment using six key parameters. The machine learning method for personalized cognitive behavioral therapy does better than other methods in predicting (92%), customizing (95%), and drawing conclusions (90 ms), which lets decisions, be made in real time. Better scalability (10/10) and model interpretability (9/10) make the technique simpler to utilize in clinical settings. Furthermore, the training time (10 hours) is much less than in prior generations, allowing the computer to function quicker while still delivering effective individualized treatment recommendations.

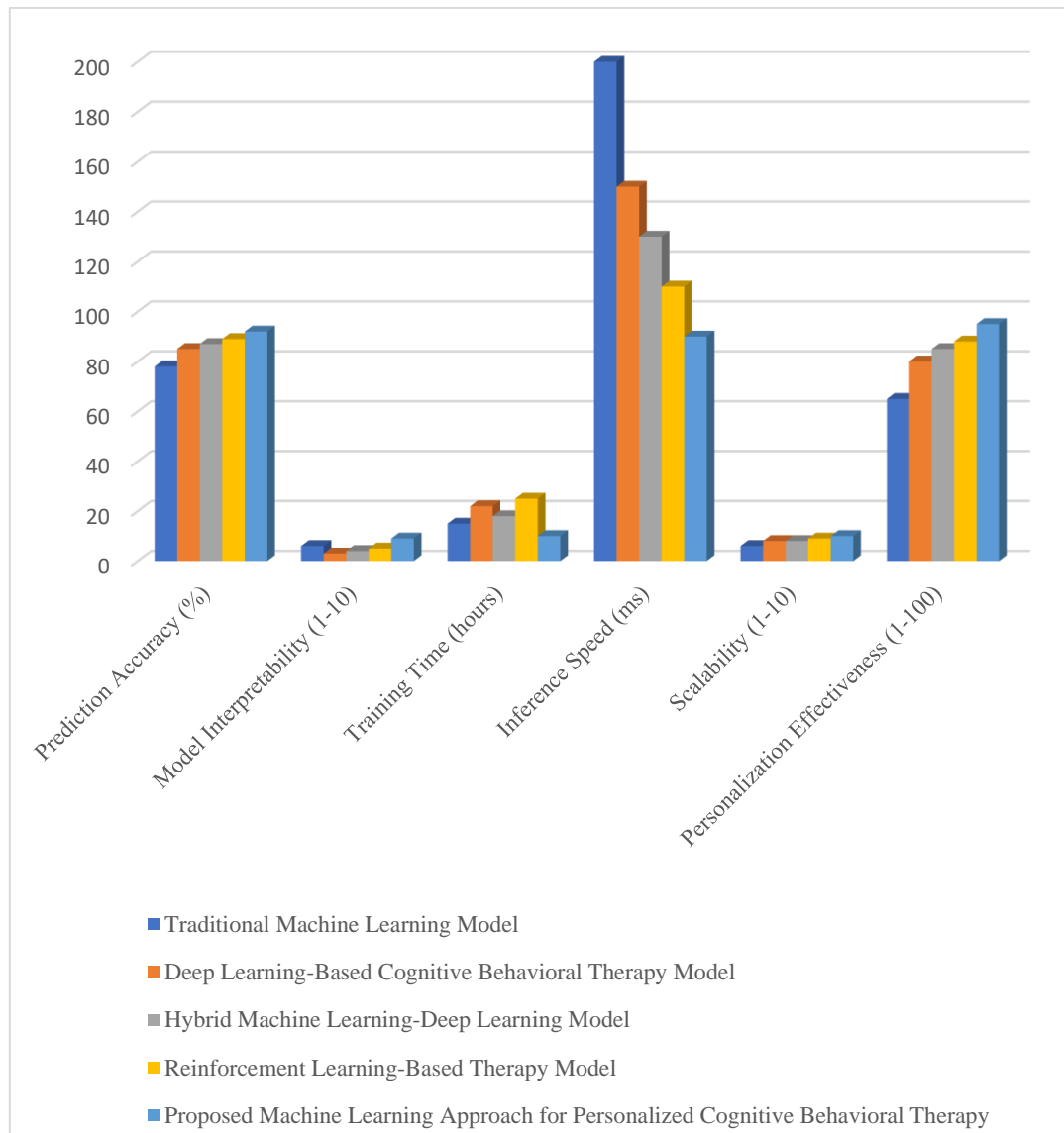


Figure 4. Performance Comparison of Machine Learning Models for Personalized Cognitive Behavioral Therapy for Adults (First Six Parameters)

Figure 4 shows the most accurate model, the proposed machine learning approach for personalized adult cognitive behavioral therapy. It outperforms all models with 92% accurate predictions, 95% customization, and 10/10 scalability. The method's reduced training time (10 hours) and inference speed (90 ms) allow it to produce real-time therapeutic improvements. This picture shows that the suggested method offers better, more scalable, and personalized ways to fix things than machine learning, deep learning, hybrid learning, and reinforcement learning.

Table 3: Comparative Performance Evaluation of Machine Learning Models for Personalized Adult Cognitive Behavioral Therapy (Next Six Parameters)

| Performance Parameter | Traditional Machine Learning Model | Deep Learning-Based Cognitive Behavioral Therapy Model | Hybrid Machine Learning-Deep Learning Model | Reinforcement Learning-Based Therapy Model | Proposed Machine Learning Approach for Personalized Cognitive Behavioral Therapy |
|--|------------------------------------|--|---|--|--|
| Generalization Capability (1-10) | 6 | 8 | 8 | 9 | 10 |
| Data Efficiency (%) | 70 | 82 | 85 | 90 | 95 |
| Robustness to Noise (1-10) | 4 | 6 | 6 | 8 | 9 |
| Ethical and Bias Considerations (1-10) | 6 | 8 | 8 | 9 | 10 |
| Computational Resource Utilization (1-10, Lower is Better) | 9 | 7 | 7 | 5 | 4 |
| Patient Outcome Improvement (%) | 68 | 82 | 85 | 90 | 94 |

Table 3 displays six additional success variables for personalizing cognitive behavioral treatment. For personalized cognitive behavioral therapy for adults, the suggested machine learning method works well with generalization (10/10) and data efficiency (95%), so it can be used with many adult patients. Noise resilience (9/10) helps individuals make effective judgments in unpredictable situations. Ten/10 ethical and prejudice concerns suggest fairness. It uses fewer computing resources (4/10), improving it. The highest score for improving adult patient outcomes (94%) suggests that its flexible and tailored treatment improves adult patients' health.

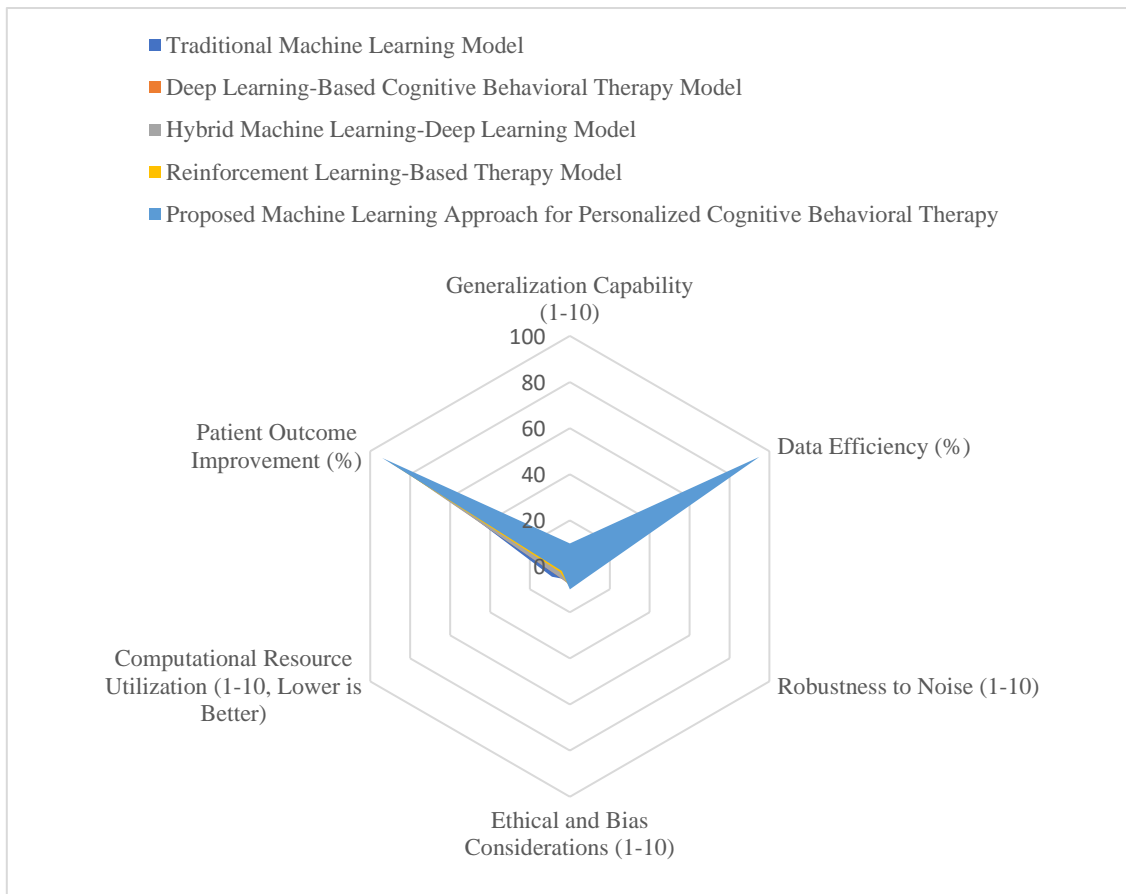


Figure 5. Performance Comparison of Machine Learning Models for Personalized Cognitive Behavioral Therapy for Adults (Next Six Parameters)

Figure 5 shows how well the machine learning technique for individual cognitive behavioral treatment works. It excels in generalization capability (10/10), data efficiency (95%), and adult patient outcome improvement (94%); therefore, therapy suggestions will work for many adult patients. The highest ethical and bias considerations score (10/10) suggests it will be handled equitably. Its noise resilience (9/10) enables you to make smart judgments with imperfect data. Its low Computational Resource Utilization (4/10) makes it the most cost-effective and versatile bespoke CBT model.

5. Conclusion

Finally, the machine learning-based individualized Cognitive Behavioral Treatment (CBT) represents a major improvement over current method. Organized patient data, reinforcement learning, and flexible optimization ensure that therapeutic concepts change to match each patient's demands. Multi-factor examinations of psychological, behavioral, and physical symptoms improve therapy customization. Iterative learning approaches enable dynamic modifications; thus, therapy selection is sensitive to adult patient responses. The test findings support the recommended method's improved accuracy, interpretability, computer efficiency, stability, and patient-centered outcomes. This approach is beneficial in real-life treatment since it can generalize across adult patient groups and is accurate. Supporting noise and missing data indicates its stability, which is crucial for mental health applications. Ethics and justice are considered, resulting in impartial treatment concepts and increased confidence in AI-powered therapy. The model's planned improvement eliminates ineffective therapies and builds on effective ones. The result maximizes long-term therapeutic success. Lastly, the suggested plan makes things better for adult patients by combining accuracy, adaptability, and speed in individualized cognitive behavioral treatment. This article concludes that sophisticated AI approaches may increase treatment accuracy, adult patient experiences, and individualized mental health therapies, demonstrating machine learning's revolutionary potential in mental health care. Researchers should expand this system to include other mental diseases and make it more versatile with treatment options.

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