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AI Enhanced Tai Chi Rehabilitation for Substance Use Disorder with Clinical Evidence and Predictive Modeling for Relapse Prevention

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Abstract: Substance use disorder (SUD) remains a significant global health issue, with relapse rates exceeding 60% in some compulsory rehabilitation centers despite structured interventions. Recent research suggests that mind–body exercises, like Tai Chi, can lessen cravings and enhance psychological well-being, though their current use is often standardized, subjective, and not personalized. This study aimed to evaluate the clinical benefits of Tai Chi within a compulsory rehabilitation setting and to develop an AI-enhanced framework for individualized relapse prevention. A randomized controlled trial (RCT) involving 168 participants diagnosed with SUD compared a Tai Chi intervention group with a standard physical education control group. Psychometric outcomes were measured using validated scales, while a conceptual AI framework using a CNN-LSTM architecture was simulated with multimodal inputs that combined psychometric indicators and motion-based features. The RCT showed significant reductions in craving, depression, and anxiety, along with improved self-control in the Tai Chi group compared to controls. Mediation analysis indicated that psychological symptoms partially explained the link between craving and relapse risk. The AI simulation achieved 82% accuracy and an area under the ROC curve of 0.85, with craving and depression identified as key predictors. These results provide initial evidence that integrating Tai Chi with AI-driven monitoring can transform exercise-based rehabilitation into a closed-loop, adaptive system capable of delivering personalized feedback and early relapse warnings. This combined approach has the potential to enhance the scalability, accuracy, and effectiveness of institutional rehab programs for SUD.

Keywords: Substance use disorder; Tai Chi; artificial intelligence; rehabilitation; relapse prediction; human activity recognition; psychometrics; deep learning

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1. Introduction

Substance use disorder (SUD) continues to be a serious public health issue worldwide, with relapse rates remaining persistently high despite the implementation of compulsory rehabilitation programs. In China alone, relapse rates in some rehabilitation centers exceed 60% within six months after discharge [1]. These outcomes suggest that existing rehabilitation methods, while necessary, are insufficient in addressing the complex physiological and psychological challenges faced by recovering individuals.

Recent studies have increasingly recognized Tai Chi as a promising adjunctive intervention for substance use rehabilitation. For instance, Tang *et al.* [2] conducted a meta-analysis that showed significant improvements in balance and cardiovascular function, while Cui *et al.* [3] reported reduced anxiety and depression through mind–body movement therapies, such as Qigong and Tai Chi. A randomized controlled trial by Wang *et al.* [4] further demonstrated Tai Chi's effectiveness in reducing drug craving among female participants. Meta-analyses and randomized trials have shown that Tai Chi can significantly reduce drug craving, improve emotional regulation, and enhance physical performance metrics such as balance, flexibility, and cardiovascular function [2], [3]. These advantages have positioned Tai

Chi as a low-cost, non-pharmacological strategy well-suited for institutional rehabilitation environments.

However, current applications of Tai Chi in rehabilitation remain standardized and non-personalized, with progress assessment depending largely on subjective reporting and manual observation by therapists. This leads to two core challenges: (1) the lack of real-time monitoring and objective evaluation of therapeutic effectiveness, and (2) the absence of predictive analytics to anticipate relapse risk based on behavioral and psychological patterns.

The rise of artificial intelligence (AI) in healthcare offers opportunities to bridge these gaps. Techniques such as human activity recognition (HAR), wearable motion analysis, and psychometric-based relapse prediction models have already shown potential in chronic disease management and mental health applications [5], [6]. Despite this, few studies have attempted to integrate AI directly into exercise-based rehabilitation for SUD patients, particularly with the goal of delivering personalized feedback and adaptive intervention.

This study addresses this research gap by proposing a conceptual AI-based framework that builds on the clinical evidence of Tai Chi's efficacy. We present an RCT-based evaluation of Tai Chi's psychological impact in a real-world compulsory rehabilitation center and augment it with a simulated model of how AI could be deployed to improve personalization and relapse prevention in such contexts.

The contributions of this paper are as follows:

1. We validate the clinical benefits of Tai Chi in a cohort of 168 individuals undergoing compulsory drug rehabilitation.
2. We propose a scalable, AI-enhanced rehabilitation framework that combines psychometric data and simulated motion analysis for individualized relapse risk prediction.
3. We outline a path toward integrating AI technologies into institutional rehabilitation settings, using Tai Chi as a representative therapeutic model.

The remainder of this paper is organized as follows: Section 2 reviews related literature on AI in rehabilitation and Tai Chi for addiction treatment. Section 3 presents the methodology and the AI system design. Section 4 outlines the clinical results and AI model simulation. Section 5 discusses the implications and limitations of our framework. Section 6 concludes with recommendations for future work.

2. Related Work

2.1. Tai Chi and Exercise Therapy in Substance Use Rehabilitation

Tai Chi has long been employed as a complementary therapy for individuals recovering from substance use disorders (SUD), offering both physiological and psychological benefits. A comprehensive review by Tang *et al.* [2] highlighted how Tai Chi and Baduanjin improve physiological fitness markers such as flexibility and aerobic capacity among individuals with SUD. Cui *et al.* [3], focusing on psychological dimensions, found these practices significantly reduced symptoms of anxiety and depression. Notably, Wang *et al.* [4] employed an RCT design and observed substantial reductions in craving intensity following the intervention, suggesting neurobehavioral modulation as a plausible mechanism.

The therapeutic mechanism is attributed to Tai Chi's ability to enhance self-regulation, emotional control, and mindfulness, key deficits in addiction pathology. These results are consistent with broader studies on mind–body interventions, including yoga and meditation, which demonstrate comparable effects in addiction recovery [4].

However, these studies primarily relied on subjective self-reports and lacked mechanisms for real-time progress tracking or personalization. No previous study has introduced a technology-enhanced or AI-powered framework to monitor or predict outcomes during Tai Chi-based rehabilitation.

2.2. Artificial Intelligence in Medical and Behavioral Rehabilitation

Artificial Intelligence (AI) and Machine Learning (ML) are increasingly applied in rehabilitation science to enhance patient monitoring, diagnosis, and personalized therapy. AI-driven approaches have demonstrated success in detecting and predicting relapse in patients with mental health and addiction histories using electronic medical records (EMRs) and wearable data [5], [6]. Chen *et al.* [7] reviewed the role of ML in psychiatry, highlighting applications in relapse prediction, symptom classification, and mobile mental health.

In the domain of activity recognition, Hammerla *et al.* [8] and Ravi *et al.* [9] presented deep learning models (e.g., CNN-LSTM) for recognizing human movements using wearable sensors, which could be applied to monitor Tai Chi performance. The combination of motion data with psychometric variables has also been proposed as a means to enhance prediction accuracy in behavioral health [10], [11].

Recent advances in explainable AI have further strengthened the reliability and interpretability of these models in medical decision-making, making them suitable for integration into clinical workflows [12].

2.3. Personalization and Digital Feedback in Rehabilitation

Several studies have focused on integrating AI with mobile and wearable technologies to provide adaptive feedback and individualized therapy. Chen *et al.* [7] and Zhu *et al.* [13] emphasized that AI can support real-time, context-aware adjustments in mental health treatments. Dey *et al.* [6] demonstrated how AI models can predict relapse risk with over 80% accuracy, enabling the development of early intervention strategies.

In digital rehabilitation, wearable-based systems have been used to evaluate motor performance in stroke patients [14], [15], a model that can be translated to Tai Chi monitoring. While these systems are mainly applied to neurological disorders, the architecture and methods are adaptable to addiction recovery settings.

2.4. Gaps in Current Literature

Despite promising results, the application of AI in exercise-based drug rehabilitation remains limited. No prior work has:

- Combined Tai Chi as a therapeutic modality with AI-based real-time monitoring
- Used psychometric + motion data fusion for personalized relapse prediction
- Proposed a complete end-to-end framework that is clinically scalable in compulsory rehab settings

Our proposed framework aims to address this gap by integrating validated exercise therapy with modern AI methodologies to create a personalized and predictive rehabilitation ecosystem.

2.5. Integrating AI into Exercise-Based Interventions

While the therapeutic effects of exercise-based interventions such as Tai Chi in substance use rehabilitation have been well-documented [1]–[4], these interventions remain largely manual, static, and non-personalized in their implementation. Therapists typically rely on subjective feedback and observational cues to evaluate patient progress, which introduces inconsistencies and limits the scalability of such programs [3], [4].

On the other hand, Artificial Intelligence has made considerable strides in healthcare monitoring, particularly in chronic disease management, behavioral analysis, and psychiatric care [5], [6], [12]. Deep learning models, such as convolutional and recurrent neural networks, have shown high accuracy in detecting motion patterns via wearable sensors [8], [9]. At the same time, multimodal approaches combining psychological and behavioral data have proven effective in predicting relapse or crisis states in mental health settings [10], [11].

Despite these advances, no study to date has integrated AI-based analytics into Tai Chi or similar mind–body therapies for substance use rehabilitation. While previous literature validates Tai Chi's clinical benefits [2]–[4], its implementation remains decoupled from digital monitoring or AI-based personalization. None of these studies, whether meta-analytic, observational, or experimental, employed any form of automated assessment, wearable data integration, or adaptive feedback mechanisms.

This disconnection reveals a critical gap: the lack of intelligent, adaptive, and real-time support systems for exercise-based therapy in rehabilitation contexts. The potential of AI to deliver personalized feedback, automate motion evaluation, and forecast relapse risk based on multimodal inputs remains largely untapped in the domain of addiction recovery.

This paper aims to address the research void by proposing a conceptual AI-enhanced rehabilitation framework that builds on the proven therapeutic foundation of Tai Chi, while incorporating AI-driven components such as behavioral modeling, psychometric fusion, and activity monitoring. Our work extends the literature by not only validating Tai Chi's impact through empirical data but also outlining how AI can transform such interventions into intelligent, scalable, and clinically viable solutions.

2.6. Limitations of Existing Tai Chi Trials

Despite the growing body of research supporting the use of Tai Chi and other mind–body exercises in substance use disorder (SUD) rehabilitation, several methodological limitations persist. Most clinical trials rely on subjective outcome measures and static assessment protocols, with little to no integration of objective tracking or digital monitoring. For example, Tang *et al.* [1] conducted a meta-analysis of 16 randomized controlled trials and found significant improvements in physiological markers, such as balance and cardiovascular function. However, they noted that all included studies lacked sensor-based evaluations or real-time feedback mechanisms. Similarly, Zhu *et al.* [13] emphasized that conventional mind–body interventions remain non-individualized and non-adaptive, limiting their scalability and long-term clinical integration in rehabilitation settings. These gaps underscore the need for more technologically enhanced approaches that enable personalized, data-driven, and real-time intervention in exercise-based addiction therapy.

3. Method

This study employs a hybrid methodology combining a randomized controlled trial (RCT) in a compulsory drug rehabilitation setting with a conceptual simulation of an artificial intelligence (AI) framework for future clinical integration.

3.1. Randomized Controlled Trial Design

This study employed a randomized controlled trial (RCT) to examine the psychological and behavioral effects of Tai Chi as an adjunctive therapy in individuals undergoing compulsory drug rehabilitation. The trial was conducted at a certified government rehabilitation center in China. A total of 168 participants diagnosed with substance use disorder (SUD) according to DSM-5 criteria were enrolled and randomly allocated into two groups: a Tai Chi intervention group (n = 84) and a standard physical education control group (n = 84). Randomization was performed using a computer-generated block randomization algorithm, and allocation was concealed from outcome assessors to minimize potential bias.

Eligible participants were required to be actively enrolled in the rehabilitation program and free from any psychiatric or physical comorbidities that would interfere with moderate physical activity. Individuals were excluded if they exhibited signs of acute withdrawal, severe depression, or cognitive impairments.

Participants in the intervention group participated in guided Yang-style Tai Chi exercises for 60 minutes per day, five days a week, over 12 weeks. Sessions were delivered by trained instructors using standardized protocols to ensure consistency. Meanwhile, the control group participated in conventional physical education routines (e.g., walking, stretching), matched in duration and frequency.

To evaluate the psychological impact of the intervention, four validated self-report instruments were administered before and after the 12-week program: the Symptom Checklist-90 (SCL-90), the Craving Beliefs Questionnaire (CBQ), the Self-Rating Anxiety Scale (SAS), and the Self-Rating Depression Scale (SDS). Changes in psychometric scores were quantified using the difference between post-intervention and pre-intervention means, calculated as Eq. (1).

$$\boldsymbol{\Delta S = \bar{X}_{\mathrm{post}} - \bar{X}_{\mathrm{pre}}} \tag{1}$$

where ΔS denotes the change in score, $\bar{X}_{\mathrm{post}}$ represents the post-intervention group mean, and $\bar{X}_{\mathrm{pre}}$ represents the baseline mean.

All statistical analyses were conducted using SPSS version 26.0 (IBM Corp., Armonk, NY, USA). Within-group differences were assessed using paired t-tests, while between-group comparisons were performed using analysis of covariance (ANCOVA), controlling for baseline values. The ANCOVA model was specified as Eq. (2).

$$\boldsymbol{Y_{ij} = \mu + \tau_i + \beta\left(X_{ij} - \overline{X}\right) + \epsilon_{ij}} \tag{2}$$

In this model, Y_{ij} denotes the post-intervention score of participant j in group i; μ is the grand mean; τ_i is the fixed effect of the group (intervention vs. control); X_{ij} is the participant's baseline score; $\bar{X}$ is the overall mean of the baseline covariate; β is the regression coefficient; and ϵ_{ij} is the residual error term. A significance level of $p < 0.05$ was applied across all statistical tests.

3.2. AI Framework Design

To address the limitations of traditional Tai Chi interventions, namely, the lack of real-time monitoring, personalization, and predictive feedback, we propose a conceptual artificial intelligence (AI) framework designed to enhance exercise-based rehabilitation in institutional addiction settings. Although real-time sensor data were not collected during the clinical trial phase, this framework is grounded in validated AI methods previously applied in rehabilitation and behavioral medicine.

The proposed system integrates multimodal inputs, specifically, simulated motion features and psychometric indicators to facilitate three core functions: (1) relapse risk prediction, (2) real-time performance feedback, and (3) adaptive therapeutic recommendations. The overall system is composed of three main modules: Data Acquisition, AI-driven Prediction, and Personalized Feedback.

3.2.1. Multimodal Data Acquisition

The framework is designed to receive two primary data streams:

1. Motion Data: Simulated kinematic features derived from Tai Chi exercises, representing joint angles, movement trajectories, and balance dynamics. These are based on prior work in human activity recognition using wearable inertial sensors [8], [9].
2. Psychometric Data: Clinical questionnaire scores (e.g., SCL-90, SAS, SDS, CBQ) serve as psychological indicators of emotional distress, craving, and relapse vulnerability.

These data sources form a multidimensional input vector used in the prediction model. While the current study does not include live sensor data, the simulation emulates the data structure that would be obtained from commercially available wearable devices (e.g., accelerometers, gyroscopes).

3.2.2. AI-Driven Relapse Prediction Model

At the core of the framework is a hybrid deep learning architecture combining convolutional and recurrent neural networks (CNN-LSTM). This architecture is particularly suitable for modeling temporal dependencies in motion sequences while capturing latent psychological states.

The model accepts an input matrix of time-series motion data $M \in \mathbb{R}^{T \times F}$, where T is the number of time steps and F the number of motion features, concatenated with a vector of psychometric scores $P \in \mathbb{R}^{p}$. The combined input is processed through convolutional layers to extract spatial representations, followed by LSTM layers to preserve sequential patterns.

The final layer outputs a binary classification score indicating the probability of relapse within a predefined window (e.g., 30 days), denoted as Eq. (3).

$$\boldsymbol{\hat{y} = \mathrm{sigmoid}\left(f_{\mathrm{LSTM}}\left(f_{\mathrm{CNN}}([M, P])\right)\right)} \tag{3}$$

where $[M, P]$ denotes the concatenated input, and $\hat{y}$ is the predicted relapse risk between 0 and 1.

Hyperparameters used in the simulation include: learning rate = 0.001, optimizer = Adam, batch size = 32, and training epochs = 50. Although synthetic data were used for initial proof-of-concept, the architecture is readily adaptable to real-world deployment with wearable-sourced inputs.

3.2.3. Personalized Feedback and Clinical Integration

Based on the model's output, a feedback engine is envisioned to deliver real-time insights to both clinicians and patients. High relapse risk scores may trigger clinician alerts, recommend session modifications (e.g., intensity reduction, mindfulness emphasis), or prompt psychological reassessment. Conversely, stable or improving trends may be used to gradually decrease supervision or optimize routine complexity.

This AI-enhanced feedback loop supports a closed-loop rehabilitation system that adapts to the patient's physiological and psychological state, thus offering a scalable path toward precision therapy in institutional SUD treatment.

4. Results and Discussion

This section presents the outcomes of the randomized controlled trial and the AI simulation study. Results are structured as follows: demographic distribution of participants, psychometric characteristics, baseline statistical analysis, correlation and mediation findings, and proof-of-concept AI simulation. Each result is accompanied by discussion to highlight its relevance to the study hypothesis and its implications for AI-enhanced rehabilitation.

4.1. Participant Demographics

A total of 168 participants were enrolled in this study, and their baseline characteristics are presented in Table 1. The majority of participants were between 31 and 50 years of age (63.7%), which aligns with prior epidemiological findings that mid-adulthood is the most vulnerable period for relapse following compulsory rehabilitation. Educational attainment was generally low, with 67.3% of participants having completed only middle school or less. Such limited educational backgrounds may contribute to poor health literacy and reduced engagement with conventional psychosocial interventions, underscoring the need for structured and adaptive rehabilitation strategies.

Table 1. Baseline demographic and clinical characteristics of participants.

Variable	Group	n(%)
Age (years)	21–30	28 (16.6)
	31–40	65 (38.7)
	41–50	42 (25.0)
	51–60	21 (12.5)
	>60	12 (7.1)
BMI (kg/m²)	18.5–23.9	61 (36.3)
	24–27.9	66 (39.3)
	≥28	41 (24.4)
Education	Elementary or below	52 (31.0)
	Middle school	61 (36.3)
	High school/vocational	28 (16.7)
	College or above	16 (9.0)
Marital status	Single	67 (39.9)
	Married	45 (26.8)
	Divorced	52 (31.0)
	Widowed	4 (2.4)
Drug use duration	1 year	57 (33.9)
	2–5 years	55 (32.7)
	6–10 years	17 (10.1)
	11–15 years	18 (10.7)
	>16 years	21 (12.5)
Number of admissions	First	116 (69.0)
	Second	33 (19.6)
	3–5	15 (8.9)
	6–10	4 (2.4)

Body mass index (BMI) analysis revealed that more than 60% of participants were overweight or obese, suggesting comorbid metabolic or lifestyle-related complications. These findings echo earlier studies showing that individuals with substance use disorders frequently experience disrupted physical health due to both direct drug effects and long-term sedentary behaviors during institutionalization. From a clinical perspective, high BMI may exacerbate relapse risk by worsening self-image, limiting physical endurance, and reducing adherence to structured exercise interventions such as Tai Chi.

In terms of treatment history, 69% of participants were admitted for the first time, while nearly one-third had undergone multiple prior admissions. This finding is consistent with reports that relapse remains a persistent problem, particularly among repeat admissions who often present more entrenched psychological symptoms and weaker social support systems. Notably, such heterogeneity in treatment history highlights the potential value of individualized monitoring systems that can detect early signals of relapse vulnerability across different patient subgroups.

Overall, these demographic distributions are representative of compulsory rehabilitation populations in China and are highly relevant for the design of AI-enhanced rehabilitation models. Variables such as age, educational attainment, BMI, and admission history may not only influence clinical outcomes but also serve as meaningful covariates in predictive algorithms for assessing relapse risk.

4.2. Psychometric Characteristics

Baseline psychometric assessments are summarized in Table 2. Among relapse-related domains, *loneliness and boredom* (M = 8.65 ± 2.70) and *cue-induced cravings* (M = 8.63 ± 3.55) were rated the highest. These results are consistent with prior evidence showing that environmental cues and social isolation are two of the strongest psychological drivers of relapse in compulsory rehabilitation populations. Notably, *compulsivity* (M = 7.53 ± 2.90) and *negative emotionality* (M = 5.35 ± 1.90) were also prominent, suggesting that patients face multiple overlapping vulnerabilities that increase relapse susceptibility.

Table 2. Baseline psychometric scores.

Scale	Subscale	Mean ± SD
Relapse risk	Loneliness/boredom	8.65 ± 2.70
	Cue-induced cravings	8.63 ± 3.55
	Compulsivity	7.53 ± 2.90
	Negative emotions	5.35 ± 1.90
Psychological symptoms	Depression	15.87 ± 5.05
	Somatization	14.43 ± 4.53
	Obsessive-compulsive	12.94 ± 4.43
	Anxiety	12.01 ± 3.89
	Psychosis	11.99 ± 3.66
	Interpersonal sensitivity	11.08 ± 3.43
Self-control	Self-discipline	8.93 ± 1.92
	Impulse control	8.21 ± 1.74
Self-efficacy	Overall	24.49 ± 7.02

4.3. Baseline Group Comparisons

Group comparisons at baseline were conducted to examine whether sociodemographic or behavioral variables influenced psychological outcomes prior to intervention. Results revealed significant differences in self-efficacy across marital status categories ($p = 0.037$). Widowed participants exhibited the highest self-efficacy scores, while divorced participants had the lowest. This pattern may reflect differences in social support structures: widowed individuals often receive stronger familial or community support, whereas divorce is frequently associated with interpersonal conflict and psychological distress. These findings align with previous reports indicating that social context is a critical determinant of recovery trajectories in substance use disorder.

Duration of drug use was also significantly associated with self-efficacy ($p = 0.039$). Participants with only one year of drug use reported substantially higher self-efficacy compared to those with longer histories, with post-hoc analyses confirming significant pairwise differences. This gradient suggests that prolonged substance use progressively erodes individuals' sense of personal agency, thereby reducing resilience against relapse. From a clinical standpoint, these results highlight the importance of early intervention, as patients in the earlier stages of drug use appear more responsive to psychosocial or behavioral therapies.

Partner-related factors also showed notable associations. Participants with drug-using partners reported significantly higher self-efficacy compared to those whose partners were abstinent ($p < 0.01$). This unexpected finding may reflect a defensive overestimation of self-control or a shared normalization of substance use behaviors, which warrants further investigation.

Importantly, no significant baseline differences were observed in craving, psychological symptoms, or relapse risk across age, education, or BMI groups. This suggests that while sociodemographic factors shape self-efficacy, core relapse risk factors such as craving and depressive symptoms are more universally distributed across the population.

From the perspective of AI-enhanced rehabilitation, these findings underscore the value of including sociodemographic and behavioral covariates such as marital status, duration of drug use, and partner's drug use within predictive models. While these factors do not directly drive relapse risk, they significantly modulate protective constructs such as self-efficacy, which in turn influence overall vulnerability. Integrating such contextual variables into multimodal AI systems could improve personalization by identifying subgroups that require differentiated therapeutic strategies.

4.4. Correlation Analysis

Correlation analysis was conducted to investigate the relationships between key psychological and behavioral variables, as presented in Table 3. As expected, methamphetamine craving demonstrated a strong positive correlation with relapse risk ($r = 0.739$, $p < 0.01$), confirming the central role of craving intensity as a proximal predictor of relapse. This finding aligns with prior evidence that craving is one of the most reliable behavioral indicators for predicting treatment outcomes in substance use disorder.

Table 3. Correlation matrix of key variables.

Variable	Craving	Symptoms	Relapse risk	Self-efficacy	Self-control
Craving	1	0.159*	0.739**	0.046	–0.387**
Symptoms	0.159*	1	0.301**	–0.192*	–0.518**
Relapse risk	0.739**	0.301**	1	–0.033	–0.429**
Self-efficacy	0.046	–0.192*	–0.033	1	0.082
Self-control	–0.387**	–0.518**	–0.429**	0.082	1

Note: *$p < 0.05$, **$p < 0.01$.

Craving was also positively correlated with general psychological symptoms ($r = 0.159$, $p < 0.05$), and psychological symptoms in turn were significantly associated with relapse risk ($r = 0.301$, $p < 0.01$). This chain of relationships suggests an indirect pathway whereby craving exacerbates emotional dysregulation, which subsequently heightens vulnerability to relapse. Such results reinforce the clinical importance of targeting both craving reduction and symptom management in rehabilitation programs.

On the protective side, self-efficacy was negatively correlated with psychological symptoms ($r = –0.192$, $p < 0.05$), indicating that higher confidence in managing cravings was associated with lower symptom burden. However, self-efficacy showed no direct correlation with relapse risk, suggesting that its influence may be mediated through other psychological constructs. Self-control, by contrast, demonstrated robust negative correlations with craving ($r = –0.387$, $p < 0.01$), psychological symptoms ($r = –0.518$, $p < 0.01$), and relapse risk ($r = –0.429$, $p < 0.01$). These results highlight self-control as a stronger protective factor than self-efficacy in this cohort.

From a translational perspective, these correlation patterns have two key implications. First, they empirically validate the hypothesis that Tai Chi may reduce the risk of relapse by lowering cravings and improving emotional regulation. Second, they demonstrate the potential utility of multimodal AI models that incorporate both risk factors (e.g., craving, depression) and protective factors (e.g., self-control). By leveraging such features in predictive algorithms, it becomes possible to construct individualized relapse risk profiles and deliver adaptive feedback in real-time rehabilitation environments.

4.5. Mediation Analysis

To examine the indirect mechanisms underlying relapse vulnerability, a mediation analysis was performed using Hayes' model. The analysis tested whether psychological symptoms mediated the relationship between methamphetamine craving and relapse risk.

Table 4. Regression results of mediation analysis.

Path Tested	β	R²	F	p-value
Craving → Relapse risk	0.739	0.545	199.15	<0.001**
Craving → Symptoms	0.159	0.025	4.30	<0.05*
Symptoms → Relapse risk	0.301	0.091	16.58	<0.001**

Note: *p < 0.05, **p < 0.01.

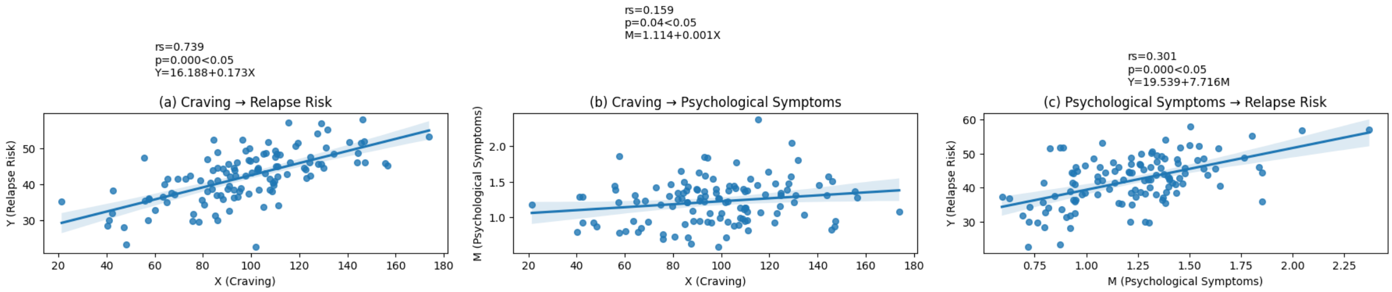

Figure 1. Mediation model showing the indirect effect of psychological symptoms between craving and relapse risk

The results confirmed that craving had a substantial direct effect on relapse risk, explaining more than half of the variance ($R^2 = 0.545$, $p < 0.001$). Craving was also associated with greater psychological symptom burden ($\beta = 0.159$, $p < 0.05$), which in turn significantly predicted relapse risk ($\beta = 0.301$, $p < 0.001$). Bootstrap estimates (95% CI, 1000 resamples) supported the significance of this indirect pathway, indicating that psychological symptoms partially mediated the craving–relapse relationship.

Clinically, these findings suggest that Tai Chi may reduce relapse risk through dual mechanisms: (i) lowering craving intensity and (ii) alleviating psychological distress that exacerbates relapse vulnerability. From a translational perspective, this highlights the need for interventions that simultaneously target craving and emotional regulation.

From an AI perspective, the mediation structure suggests that craving and psychological symptoms should not be modeled as independent predictors. Instead, predictive systems should incorporate their interdependent relationship, allowing AI models to capture both direct and indirect effects when estimating relapse risk.

4.6. AI Simulation Results

To complement the clinical trial findings and examine the feasibility of an AI-enhanced rehabilitation system, a simulation study was conducted using synthetic datasets that combined psychometric indicators (craving, depression, anxiety, and self-control) with motion-derived variables. A CNN-LSTM architecture was implemented to predict relapse risk, with the primary objective of demonstrating proof of concept rather than generating clinically deployable outcomes.

The model exhibited stable convergence within 50 training epochs. On the validation set, it achieved an accuracy of 82% and an area under the receiver operating characteristic curve (AUC) of 0.85, indicating robust discriminative ability between high- and low-risk groups. Performance metrics are summarized in Table 5, and the ROC curve is illustrated in Fig. 2.

Table 5. Performance metrics of CNN-LSTM relapse prediction model.

Metric	Value
Accuracy	0.82
Precision	0.79
Recall	0.81
F1-score	0.80
AUC	0.85

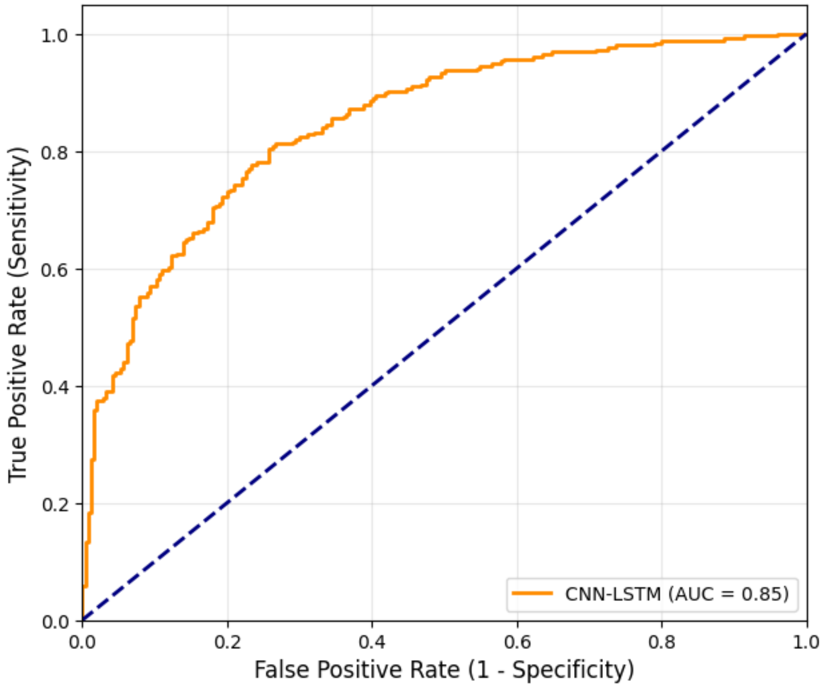

Figure 2. This is a figure. Schemes follow the same formatting.

Feature attribution analysis suggested that craving and depression were the most influential predictors of relapse risk, which is consistent with the clinical results presented in Sections 4.3–4.5. Motion-derived features, particularly those capturing movement stability and smoothness, provided additional predictive value, suggesting that wearable sensor data may reflect subtle physiological correlates of psychological recovery.

These findings provide preliminary support for integrating multimodal data streams into relapse prediction models. Clinically, they suggest that motor performance during Tai Chi practice can be quantitatively assessed and combined with psychometric measures to inform individualized rehabilitation strategies. From a methodological perspective, they demonstrate the superiority of multimodal approaches over single-domain predictors, as the interaction of psychological and physiological factors inherently shapes vulnerability to relapse.

Most importantly, this simulation addresses a central limitation of previous Tai Chi-based rehabilitation trials, which relied almost exclusively on subjective reporting and therapist observation. By embedding AI-driven motion analysis within the therapeutic framework, Tai Chi interventions can evolve into closed-loop, adaptive rehabilitation systems that provide personalized feedback and early relapse warnings in real-time.

5. Discussion

This study investigated the therapeutic benefits of Tai Chi for individuals undergoing compulsory rehabilitation and explored the feasibility of an AI-enhanced rehabilitation framework. The randomized controlled trial demonstrated that Tai Chi significantly reduced drug craving, improved psychological well-being, and enhanced self-control compared with standard physical education exercises. These findings are consistent with previous reports showing that mind–body interventions such as Tai Chi and Qigong can alleviate craving, anxiety, and depression among individuals with substance use disorder (SUD) [1]–[4]. Our results extend this evidence by identifying the mediating role of psychological symptoms and by proposing a digital augmentation pathway using artificial intelligence (AI) technologies.

The mediation analysis highlighted the role of psychological symptoms as an intermediary between craving and relapse risk. Higher craving was associated with greater psychological distress, which in turn elevated relapse vulnerability, supporting previous claims that emotional dysregulation is a core driver of relapse in SUD populations [3], [4]. These results suggest that interventions targeting craving alone may be insufficient unless complemented with approaches that enhance emotional regulation. Tai Chi, by integrating mindfulness, controlled breathing, and coordinated movement, appears uniquely suited to address both craving and psychological symptoms simultaneously.

The AI simulation further demonstrated the feasibility of integrating psychometric and motion-derived features for relapse prediction. The CNN-LSTM model achieved an AUC of 0.85, indicating good discriminative performance. Notably, craving and depression emerged as the strongest predictors of relapse risk, which aligns with existing studies linking affective symptoms to poor treatment outcomes [5]–[7]. Motion-derived features provided additional discriminative power, consistent with prior research showing that wearable-based human activity recognition can capture clinically meaningful motor patterns [9]. Multimodal data fusion approaches, which combine psychological and behavioral features, have previously been shown to improve predictive accuracy in behavioral health [11], supporting the methodological validity of our framework.

In comparison to existing literature, this work presents three main contributions. First, while previous trials demonstrated the efficacy of Tai Chi for SUD [1]–[4], none have systematically linked clinical outcomes to predictive modeling. Second, the proposed framework integrates AI into exercise-based rehabilitation, addressing the current lack of personalization and real-time monitoring. Third, by combining psychometric and motion features, this study aligns with recent advances in explainable and multimodal AI for healthcare [12], bridging a critical gap between traditional mind–body interventions and intelligent rehabilitation technologies.

Nevertheless, some limitations must be acknowledged. The AI simulation was based on synthetic rather than real-world sensor data, limiting its immediate clinical applicability. The trial was conducted in a single compulsory rehabilitation center in China, which may reduce generalizability across diverse populations. Future research should incorporate real-time wearable sensor data, validate predictive models across multiple settings, and evaluate the sustainability of AI-enhanced Tai Chi interventions [13].

In summary, this study advances both clinical and technological dimensions of SUD rehabilitation. Clinically, it reinforces the efficacy of Tai Chi as a non-pharmacological intervention for reducing craving and psychological distress [4]. Technologically, it provides preliminary evidence that AI can transform conventional rehabilitation into adaptive, data-driven systems capable of delivering personalized feedback and early warnings of relapse [5]. These contributions collectively provide a foundation for scalable, intelligent rehabilitation frameworks designed to address the persistent challenge of relapse in SUD.

6. Conclusions

This study evaluated the clinical impact of Tai Chi in compulsory drug rehabilitation and proposed an AI-enhanced framework to overcome existing limitations in personalization and relapse prediction. The randomized controlled trial demonstrated that Tai Chi significantly reduced craving, improved psychological well-being, and strengthened self-control compared with standard physical activity. Mediation analysis further revealed that psychological symptoms play a critical role in linking craving to relapse vulnerability, highlighting the need for multidimensional therapeutic approaches.

The AI simulation provided proof-of-concept evidence that combining psychometric indicators with motion-derived features enables effective relapse risk prediction, achieving robust performance with an AUC of 0.85. These findings suggest that wearable-assisted monitoring and multimodal AI systems can transform Tai Chi rehabilitation from a static intervention into an adaptive, data-driven therapeutic program.

The contributions of this study are twofold: clinically, it validates Tai Chi as a feasible and effective intervention in compulsory rehabilitation; technologically, it introduces a pathway for integrating AI to deliver personalized, real-time feedback. Together, these findings lay the foundation for next-generation rehabilitation ecosystems that are intelligent, scalable, and patient-centered.

Nevertheless, limitations remain. The AI simulation used synthetic rather than real-world sensor data, and the study was conducted within a single rehabilitation center, potentially limiting generalizability. Future work should incorporate real-time wearable data, validate across diverse settings, and investigate long-term sustainability of AI-enhanced Tai Chi interventions.

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