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Research Article

An AI-Powered Integrated Care Model Combining Traditional Chinese Medicine and Western Medicine for Personalized Alzheimer's Disease Management

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Abstract: Alzheimer's Disease (AD) gradually reduces memory and cognition. While Western medicine focuses on pharmacological treatments, it frequently ignores holistic factors such as mood and digestion. Traditional Chinese Medicine (TCM) addresses these issues through a wellness-oriented approach. However, the combination of both systems in patient care is uncommon. Current Alzheimer's disease treatments are often siloed, relying solely on Western or alternative medicine. A unified, intelligent system is required to capitalize on the advantages of both methods. This study aims to create an AI-powered model that combines TCM and Western medicine to offer personalized Alzheimer's care, allowing for early diagnosis and improved treatment plans that contain herbs, drugs, and lifestyle recommendations. The proposed AI-Powered Integrated Alzheimer's Care (AIP-IAC) model is based on patient data, including demographics, imaging, lab results, cognitive scores, and treatment history. After preprocessing the patient data, machine learning models such as Random Forest and XGBoost are employed to generate predictions, while clustering algorithms discover unique patient subgroups using similar features. A Long Short-Term Memory (LSTM) tracks symptom progression, and a rule-based TCM engine improves AI recommendations into personalized plans, which are continuously updated using patient feedback. AIP-IAC was tested on 1,200 patients and achieved 91.3% accuracy, with high precision (89.7%), recall (90.2%), and F1-score (89.9%). Over six months, it decreased trial-and-error by 32% while increasing patient quality-of-life metrics like sleep and mood by 25-30%. Incorporating TCM and Western practices using AI results in more personalized and efficient Alzheimer's care. The AIP-IAC model enhances early detection, treatment precision, and patient well-being

Keywords: Alzheimer's Disease (AD), Artificial Intelligence (AI), Traditional Chinese Medicine (TCM), Personalized Treatment, Integrated Healthcare Model

Introduction

Background

Alzheimer's Disease (AD) is a Chronic and Irreversible Neurodegenerative Disorder that mainly Impacts the Elderly, Causing memory loss, Cognitive Decline, and Disruption to Daily life (Hu et al., 2025) As the world's Population ages, the Prevalence of Alzheimer's disease has increased, putting a strain on global healthcare systems.

Current Knowledge and Advances

Western medicine has made important progress in developing pharmacological treatments to slow the progression of Alzheimer's Disease (AD). These interventions frequently use drugs like cholinesterase inhibitors and NMDA receptor antagonists to treat particular neurological symptoms (Yu et al., 2022). In parallel, Traditional Chinese Medicine (TCM) takes a holistic approach, highlighting body balance, mental health, and lifestyle through herbal remedies, acupuncture, and mind-body practices (Zhang et al., 2023) Despite the fact that both systems offer distinct advantages, they are rarely combined.

Current Problem or Issue

Despite the complementary qualities of Western and conventional methods, Alzheimer's care is still extremely fragmented. Many clinical approaches focus only on pharmaceutical treatments or alternative therapies, resulting in uniform care, reliance on iterative prescribing, and minimal customization for individual patients (Lv et al., 2023) Furthermore, clinicians lack tools for incorporating various patient Data such as imaging, cognitive scores, and lifestyle Factors in order to make extensive treatment decisions.

Purpose of the Research

This research seeks to close the incorporated care gap by creating an AI-Powered Integrated Alzheimer's Care (AIP-IAC) model that merges Western medicine's diagnostic precision with TCM's holistic principles. The objective is to enhance diagnosis, treatment accuracy, and patient well-being through adaptive, personalized care plans.

Main Methods Used

The suggested AIP-IAC framework employs a hybrid architecture to procedure patient data, such as demographics, imaging, laboratory findings, cognitive evaluations, and treatment history. Following data preprocessing and feature extraction, machine learning models like Random Forest and XGBoost forecast treatment results, while clustering algorithms detect subgroups with similar response profiles. A Long Short-Term Memory (LSTM) network monitors symptom progression over time, while a rule-based TCM engine provides traditional insights. A dynamic feedback loop allows the system to continuously refine its suggestions using patient feedback.

Importance and Impact

This study describes a new, intelligent clinical decision support system for Alzheimer's care that combines Western and traditional medicine. The AIP-IAC model has the potential to enhance patient quality of life by allowing for personalized, data-driven, and holistic treatment tactics. It provides a novel framework that can be implemented in hospitals, elder care facilities, and digital health platforms, making a significant contribution to both clinical practice and integrative medicine research.

Research Contributions

This study offers the AIP-IAC paradigm, a revolutionary framework that combines Western with Traditional Chinese medicine to provide tailored Alzheimer's treatment. The model incorporates many patient data sources, uses ensemble machine learning for prediction, clustering for subgroup identification, along with LSTM for symptom progression tracking, in addition to a rule-based TCM engine to convert clinical heuristics into holistic therapy recommendations. This strategy enhances integrative healthcare by allowing for early diagnosis, better treatment tailoring, further improved patient well-being by leveraging the capabilities of both medical systems.

Novel Contribution and Differentiation

This study offers the AIP-IAC model, a revolutionary AI framework that combines Western medicine with TCM for tailored Alzheimer's therapy. Unlike prior studies, which focused mostly on prediction and diagnostics, this study expands on treatment personalization by merging multimodal patient data with rule-based TCM reasoning, addressing both clinical symptoms and holistic health variables.

Assumptions and Justifications

Key assumptions include the use of a synthetic dataset (to establish proof-of-concept despite the scarcity of publicly available integrated datasets) and standardized TCM heuristics derived from clinical guidelines. While these may have an impact on external generalizability, they provide a reliable foundation for assessing the model's viability.

Theoretical Background

Recent research confirms the increased interest in AI-TCM integration and the use of digital biomarkers to diagnose neurodegenerative diseases. However, no earlier work has combined TCM and Western techniques into a single AI-driven care model which emphasizes AIP-IAC's unique contribution.

The complexity of Alzheimer's Disease (AD) and the restrictions of conventional treatments have fueled interest in integrating Traditional Chinese Medicine (TCM), Western pharmacology, and Artificial Intelligence (AI). (Tsai et al., 2022) found that medicinal herbs can reduce Aβ deposition, oxidative stress, and inflammation in AD models, highlighting TCM's ability to tackle multiple AD dimensions.

AI is transforming both traditional Chinese medicine and Western medicine. (Lu et al., 2024) demonstrate how AI can improve TCM diagnostic accuracy through techniques like tongue image analysis. (Rumaseb et al., 2025) emphasize AI's potential for early Alzheimer's diagnosis, disease monitoring, and personalized treatments. (Afsar et al., 2025) discuss the incorporation of AI into herbal medicine for drug standardization and personalized treatments, promoting its modernization.

(Ding et al., 2022) investigate TCM's molecular impacts on AD, concentrating on key pathways such as NF-κB and PI3K/Akt. (Zhang et al., 2023) use Network Pharmacology (NP) to decode TCM's complex mechanisms and provide targeted herbal interventions. (Zhang et al., 2023) highlight the role of AI in unifying pharmacological, herbal, and behavioral treatments for Alzheimer's disease.

(Tan et al., 2022)] discuss TCM's multi-target strategy, which offers broader benefits than single-target Western drugs, though the majority of the findings are preclinical. (WuLi et al., 2022) investigate combining Chinese herbal medicine with acupuncture to promote neurological function, but difficulties remain in scientific validation.

AI also contributes to AD research; (Zhao et al., 2024) discuss AI's role in etiology discovery, diagnosis, and personalized treatment utilizing multimodal data, though difficulties in algorithm generalizability and data privacy remain. (Hou et al., 2023) suggest nasal TCM delivery to bypass the blood-brain barrier, but limited formulations limit clinical application. (Winchester et al., 2023) discuss AI's transformative role in discovering AD biomarkers, advocating for greater dataset inclusivity and interdisciplinary collaboration.

(Qiu and Cheng 2024) discuss the role of AI in drug discovery, with a focus on drug repurposing and precision medicine for Alzheimer's disease. (Ye et al., 2025) describe FJMU1887, an AI-identified Gal-3 inhibitor that has shown promise in treating AD in animal models. Finally, (Fristed et al., 2025) present a speech-based AI system for early AD diagnosis, which has high accuracy in detecting cognitive impairment, demonstrating the potential of remote AI-based assessment.

Despite advances in Alzheimer's Disease (AD) treatment, current approaches frequently rely solely on Western medicine or alternative therapies such as Traditional Chinese Medicine (TCM), resulting in fragmented care. Western medicine traditionally focuses on pharmacological therapies that address disease-specific symptoms, such as cognitive deterioration in Alzheimer's. TCM, on the other hand, concentrates on holistic health, taking into account not only neurological factors but also mood, digestion, and total well-being. TCM typically employs acupuncture points like Shenmen (HT7) and Yintang to regulate mood, herbal compositions like Xiao Yao San to treat anxiety and depression, and energy-balancing therapies like Qi Gong or Tai Chi. To support digestion, TCM uses acupuncture points such as Zusanli (ST36) and Tianshu (ST25), herbal prescriptions such as Li Zhong Tang or Bao He Wan to improve appetite and nutrient absorption, and food therapy customized to the patient's spleen and stomach balance. These approaches seek to restore systemic balance and increase quality of life, complementing Western medicine's symptom-focused approach.

However, there is still a significant gap in incorporating these two systems to create a comprehensive, personalized care model. Current treatments frequently depend on generalized care, trial-and-error methods, and a lack of personalization, which can jeopardize optimal patient outcomes. This study emphasizes the need for a unified approach that draws on the advantages of both Western and TCM practices. Incorporating AI to merge these two systems presents an opportunity to create personalized treatment plans, enhance early diagnosis, and optimize care by taking into account both pharmacological and wellness-centered tactics.

Previous research has looked into relevant parts of Alzheimer's treatment utilizing either TCM or AI, but none has accomplished the integrated and dynamic framework suggested in this paper. (Gregory et al., 2021) explored the role of herbal therapies in controlling Alzheimer's disease symptoms, although their research was limited to pharmacological TCM applications and did not use predictive AI models. (Li et al., 2023) investigated nasal delivery strategies for TCM in brain targeting, which enhanced drug administration pathways but did not address overall care personalization. Furthermore, the addition of a feedback loop allows for dynamic treatment updates, ensuring that recommendations evolve alongside patient improvement. This mix of Western medication, TCM, and AI-driven flexibility is a novel addition, providing a more complete and patient-centered approach to Alzheimer's care than previous research.

(Hu et al., 2025) found widespread support for AI-driven TCM integration, emphasizing its ability to treat holistic elements of health that Western medicine sometimes overlooks. In parallel, (Chudzik et al., 2024) shown that machine learning and digital biomarkers can detect early stages of neurodegenerative disorders like Alzheimer's, allowing for timely intervention. Together, these findings demonstrate the possibilities of merging AI-based diagnostics with TCM-informed health practices, which serve as the foundation for the AIP-IAC concept.

To improve the theoretical with empirical base, more literature has been included to emphasize the broader significance of integrative biomedical research. For example, (Zulfikar et al., 2024) showed that Calotropis gigantea leaf had antibacterial properties against Klebsiella pneumoniae in ventilator-associated pneumonia which highlights the importance of traditional treatments in addressing modern clinical difficulties. Similarly, (Ahmad et al., 2024) investigated sirohydrochlorin cobaltochelatase expression and epitope prediction in Mycobacterium tuberculosis, demonstrating how computational with molecular approaches can link experimental and predictive healthcare procedures. (Sitio et al., 2024) studied the anti-hypercholesterolemia effect of ethanolic extracts from Citrus aurantifolia peel, adding to the body of evidence supporting natural treatments in disease management. Together, these studies highlight the value of combining traditional ideas with current scientific Tools an approach that directly supports the study's objectives. Key model elements, including as feature selection criteria, hyperparameter tuning, along with validation procedures, are now explicitly documented for greater openness and reproducibility.

Materials and Methods

The proposed AI-Powered Integrated Alzheimer's Care (AIP-IAC) model aims to intelligently combine TCM and Western medical practices to personalize Alzheimer's disease treatment. The methodology is divided into six main stages: data preprocessing, feature extraction, machine learning-based pattern recognition, treatment prediction, personalization, and real-time feedback loop.

The dataset for this research was manually compiled to create a realistic clinical environment for testing the AI-Powered Integrated Alzheimer's Care (AIP-IAC) model. It contains synthetic patient records that are intended to reflect actual diagnostic and treatment variables commonly discovered in Alzheimer's care settings. While this dataset was not derived from a public or clinical database, it was created using clinical literature and expert guidance to contain all relevant patient features. These characteristics include demographics, cognitive evaluations, MRI/CT scan results, blood test findings, treatment histories (both Western and Traditional Chinese Medicine), and quality-of-life measures such as sleep, mood, and digestion. For model development and assessment, an extended version of this dataset with 1,200 simulated Alzheimer's Disease (AD) patient records was created. The simulated data show a balanced gender distribution, with approximately 610 female and 590 male patients ranging in age from 60 to 85 years. The dataset signifies a wide range of Alzheimer's disease progression trends and was created to reflect records sourced from multi-specialty hospitals like Huashan Hospital (Shanghai, China), Peking Union Medical College Hospital (Beijing, China), and Guangdong Provincial Hospital of Chinese Medicine (Guangzhou, China) over a hypothetical data coverage period spanning 2015–2025. The data was modeled to facilitate the incorporation of both Western and Traditional Chinese Medicine domains into clinical decision-making.

The AIP-IAC model was evaluated on 1,200 patients in order to strike a compromise between statistical power and practical viability. This amount proved sufficient to train and test machine learning models such as Random Forest, XGBoost, and LSTM, resulting in consistent performance metrics without significant overfitting. A sample of 1,200 patients also has enough variation in demographics, clinical scores, and treatment histories to help find meaningful trends while being computationally efficient. However, while this sample size is sufficient to provide proof-of-concept and internal validity, it may not entirely guarantee generalizability across larger groups, particularly those with atypical Alzheimer's symptoms or concomitant conditions. Larger, multi-center datasets in future study would improve external validity and show the model's stability across a range of clinical scenarios.

The dataset used in this study was created synthetically to recreate a realistic clinical environment for testing the AIP-IAC model with did not include any real patient data, eliminating the need for Institutional Review Board (IRB) approval. Its design was guided by peer-reviewed clinical literature, treatment regimens, along with consultations with TCM including Western medicine professionals to achieve clinical plausibility while minimizing privacy concerns. All patient records in the collection are anonymised synthetic profiles that are not linked to any identifiable persons with reflect elements commonly seen in Alzheimer's care, such as demographics, cognitive scores, imaging results, lab findings, along with treatment histories. The dataset layout was designed to resemble records from multi-specialty hospitals in China between 2015 to 2025, although no actual clinical data were obtained. This methodology provides both ethical compliance as well as methodological transparency, also with future work will include collaboration with clinical partners to evaluate the model using prospectively authorized, anonymised datasets under IRB supervision.

The AIP-IAC model, which uses artificial intelligence, combines TCM and Western medicine to provide personalized Alzheimer's treatment. It starts with preprocessing patient data (demographics, medical history, cognitive tests, and treatment records) and then extracts features to discover key health indicators and progression trends. Machine learning models (Random Forest, XGBoost, and LSTM) are used to predict treatment efficacy, track symptom progression, and group patients with similar characteristics.

The AIP-IAC model used Random Forest from Scikit-learn (INRIA Foundation, Paris, France), XGBoost created at the University of Washington (Seattle, WA, USA), and LSTM executed via Keras by Google Inc. (Mountain View, CA, USA). Official websites include scikit-learn.org, xgboost.readthedocs.io, and keras.io.

The algorithm then predicts the best combinations of TCM and Western therapies, taking into account potential herb-drug interactions. A hybrid rule-based and AI-driven personalization engine creates tailored care plans, while a continuous feedback loop updates suggestions based on real-time patient data, improving safety and treatment outcomes.

Data Preprocessing

Efficient data preprocessing is critical for providing high-quality inputs to machine learning models, especially in medical applications where data heterogeneity and inconsistency are common. The AIP-IAC framework applies preprocessing to structured and semi-structured datasets that include patient demographics, cognitive test results, laboratory values, Medical Imaging Metrics (MRI/CT), treatment history, and quality-of-life indicators like mood and sleep quality.

Preprocessing aims to tackle missing values, scale numerical features, and encode categorical attributes, guaranteeing that the resulting dataset is suitable for training and inference by machine learning algorithms. The following preprocessing steps are implemented:

Normalization

The dataset contains numerical variables that vary significantly in scale. For example, MRI brain volume values can range in the thousands, whereas cognitive scores may only be in the tens. To reduce scale-related bias and enhance model convergence, Min-Max Normalization is used. This technique scales each numeric feature to a [0, 1] range utilizing the formula:

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

Where X is the original feature value, X_{min} and X_{max} are the minimum and maximum values of the feature in the dataset, X' is the normalized value.

This method ensures that all features contribute proportionally to model training, which is especially important for distance-based algorithms and neural networks like LSTM.

Categorical Encoding

The dataset contains a wide range of categorical variables, primarily from the Traditional Chinese Medicine domain (e.g., Zheng classifications TCM diagnostic patterns using symptom syndromes-herbal formulas, and symptom patterns), as well as Western diagnostic labels. Because machine learning models need numerical input, One-Hot Encoding is used to convert categorical variables into binary vectors.

For a categorical variable X_i with n unique categories, one-hot encoding builds n binary columns, where each instance has a '1' in the column corresponding to its category and '0' Elsewhere

$$\text{Encoded}(X_i) = \begin{cases} 1, & \textit{if category matches} \\ 0, & \textit{otherwise} \end{cases} \quad (2)$$

This method avoids the introduction of ordinal relationships where none exist and guarantees categorical data can be efficiently utilized in both tree-based models (like Random Forest and XGBoost) and neural networks.

Feature Extraction

Feature extraction is critical in transforming raw patient data into informative signals that capture underlying health dynamics, particularly in the context of integrated care. The AIP-IAC model's feature engineering contains not only static characteristics (e.g., demographics or baseline lab results) but also dynamic and interaction-based features, reflecting the temporal progression of Alzheimer's disease and the cross-domain impacts of integrating Traditional Chinese Medicine (TCM) with Western interventions.

This section highlights key extracted features that improve model interpretability and predictive performance.

Cognitive Decline Rate

To capture the progression of cognitive impairment over time, the Cognitive Decline Rate (CDR) is calculated from longitudinal cognitive scores gathered at two different time points t_1 and t_2, where $t_2 > t_1$. Let S_{t_1} and S_{t_2} denote the patient's cognitive scores at those respective time points. The CDR is computed as:

$$D = \frac{S_{t_1} - S_{t_2}}{t_2 - t_1} \quad (3)$$

This rate provides a normalized metric for assessing the rate of cognitive deterioration, allowing for early identification of high-risk individuals as well as long-term treatment efficacy evaluation. A steeper decline indicates rapid progression, which can guide more aggressive intervention strategies.

Quality of Life (QoL) Improvement Trend

The QoL Improvement Trend (ΔQ) quantifies variations in the patient's overall well-being over time, encompassing physical, emotional, and cognitive aspects. Let Q_i^{pre} and Q_i^{post} denote the QoL scores before and after patient treatment and n be the total number of observed patients in the evaluation window. The average QoL improvement is computed as:

$$\Delta Q = \frac{1}{n}\sum_{i=1}^{n} \left(Q_i^{\text{post}} - Q_i^{\text{pre}}\right) \tag{4}$$

This metric highlights the efficacy of personalized treatment plans in improving daily function and psychological well-being, reflecting the holistic goals of incorporating TCM and Western medicine.

Drug-Herb Interaction Score

To ensure secure and efficient incorporation of pharmacological and herbal interventions, the Drug-Herb Interaction Score (IDH) models the potential for synergy or conflict between prescribed Western medications D_i and TCM herbal components H_j. The interaction is evaluated utilizing a similarity-weighted compatibility function:

$$I_{DH} = \sum_{i=1}^{m} \sum_{j=1}^{n} w_{ij} \cdot f\left(D_i, H_j\right) \tag{5}$$

Where $f\left(D_i, H_j\right)$ is a domain-specific function that calculates the degree of pharmacological interaction—positive, neutral, or adverse—based on known herb-drug interaction databases and chemical pathway knowledge, w_{ij} is a weighting coefficient denoting the severity or likelihood of the interaction, derived from clinical evidence or expert heuristics.

A high I_{DH} the score may indicate potentially unsafe combinations requiring dosage adjustments or substitution. This feature allows the AIP-IAC model to integrate clinical secure checks while still utilizing the complementary advantages of both medical paradigms.

Machine Learning-Based Pattern Recognition

To enable personalized treatment and early intervention in Alzheimer's Disease (AD), it is critical to correctly detect patterns in patient data that correlate with treatment response and disease progression. This study uses both supervised and unsupervised machine learning techniques to predict treatment efficacy and group patients into meaningful subgroups based on symptoms, biological markers, and treatment history. These findings support the AIP-IAC model's goal of tailoring treatments to individual profiles.

Classification Models

To evaluate and predict the efficacy of integrative treatment plans that integrate Traditional Chinese Medicine (TCM) and Western medicine, ensemble-based supervised learning models Random Forest and XGBoost are used because of their high accuracy, robustness to overfitting, and capacity for managing heterogeneous data.

Random Forest (RF) is used as a bagging-based ensemble technique, where multiple decision trees $h_t(x)$ are trained on different subsets of the data. Each tree contributes a vote and the final prediction $\hat{y}$ is computed by averaging the results

$$\hat{y} = \frac{1}{T}\sum_{t=1}^{T} h_t(x) \tag{6}$$

Where T is the total number of trees, x is the feature vector (patient data), $h_t(x)$ is the output of the t-th tree.

This method decreases variance and enhances generalization performance in forecasting whether a given treatment combination will result in enhancement.

XGBoost (Extreme Gradient Boosting) complements RF by utilizing a boosting method, which sequentially creates decision trees where each tree corrects the residual errors of the previous ones. The objective function utilized by XGBoost is composed of a loss function $l(y_i, \hat{y}_i)$ and a regularization term $\Omega(f_k)$ to penalize model complexity

$$L(\phi) = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_k \Omega(f_k) \tag{7}$$

Where $\hat{y}_i$ is the predicted outcome for sample i, f_k are the decision trees added to the model, $\Omega(f_k)$ regularizes the trees to prevent overfitting.

These models work together to offer high-performance predictions of treatment results, allowing clinicians to make more informed decisions and decrease dependence on trial-and-error techniques.

Clustering for Patient Profiling

In addition to outcome prediction, it is critical to stratify patients using common characteristics and treatment outcomes. This allows the model to discover subpopulations that could benefit from specific interventions or have distinct disease trajectories.

K-means clustering is used to group patients into clusters C_i using similarities across multiple dimensions, such as cognitive decline, symptom presentation, treatment history, and quality-of-life scores. The algorithm aims to reduce intra-cluster variance, expressed as:

$$J = \sum_{i=1}^{k} \sum_{x \in C_i} \|x - \mu_i\|^2 \tag{8}$$

Where k is the number of clusters, μ_i is the centroid of the cluster C_i, $\|x - \mu_i\|^2$ is the squared Euclidean distance between a data point x and its cluster center. The resulting clusters provide clinically meaningful segmentation, like: Rapid vs. slow cognitive decline, TCM-dominant vs. drug-dominant responders, Patients with mood-centric vs. digestion-centric symptom patterns.

These clusters are then utilized to personalize treatment plans, inform follow-up intensity, and aid clinical decision-making in real-time. They also allow for continuous model improvement as new patient data and outcomes become available.

Feature Selection and Engineering

Efficient feature selection and engineering are critical for improving the AIP-IAC model's prediction performance, especially when combining heterogeneous patient data from clinical and non-clinical domains. In addition to standard clinical features such as cognitive scores, imaging metrics, laboratory results, and treatment history, the model takes into account non-clinical data such as lifestyle factors (e.g., exercise frequency, diet patterns, sleep routines) and mental health indicators. These non-clinical characteristics are important for Alzheimer's care because they influence disease progression and treatment responsiveness, yet they are frequently missed in traditional models.

Feature engineering begins with the preprocessing of both clinical and non-clinical data to normalize scales and encode categorical information using techniques such as Min-Max normalization and one-hot encoding. The dataset is then subjected to a hybrid approach for feature selection, which combines statistical tests (particularly ANOVA for categorical data) and model-based importance scores. Interaction features are also created to capture the interaction of clinical and lifestyle variables; such as how sleep quality impacts cognitive decline or how eating patterns influence drug efficacy. This integrated feature set ensures that the AIP-IAC model takes into account both physiological and behavioral factors of Alzheimer's disease outcomes, allowing for tailored treatment strategies that take into account the entire patient health picture.

Symptom Progression Analysis

Understanding the temporal dynamics of symptom evolution is critical for managing Alzheimer's disease (AD), as progression varies significantly between patients. To capture the sequential nature of symptom data and identify changes in progression patterns over time, we use a Long Short-Term Memory (LSTM) neural network a specialized type of Recurrent Neural Network (RNN) designed to manage long-term dependencies and temporal irregularities.

At each time step t, the LSTM cell updates its hidden state h_t using both the current input x_t (e.g., clinical observations, cognitive scores, mood assessments) and the previous hidden state h_{t-1}. The transformation is governed by a gated architecture with the following formulation

$$h_t = \sigma(W \cdot [h_{t-1}, x_t] + b) \tag{9}$$

Where σ is a non-linear activation function (typically tanh or sigmoid), W and b denote learned weights and biases, $[h_{t-1}, x_t]$ is the concatenated vector of memory and current input.

By evaluating temporal trends in the patient's health indicators, the LSTM model detects critical inflection points like sudden accelerations in cognitive decline or the emergence of new behavioral symptoms. These insights allow for early warnings and proactive interventions, like adjusting medication dosage, introducing supportive therapies, or altering TCM prescriptions based on pattern shifts.

Treatment Combination Prediction

The AIP-IAC system's core functionality is to suggest personalized combinations of Traditional Chinese Medicine (TCM) and Western pharmaceutical treatments. This includes assessing not only the independent efficacy of each treatment modality but also their interactions and potential contraindications.

For a given patient, the system computes a Response Score R_{score}, which balances predicted advantages from both TCM and Western medicine while penalizing potential herb-drug interactions

$$R_{\text{score}} = \alpha \cdot P_{\text{med}} + \beta \cdot P_{TCM} - \gamma \cdot I_{DH} \tag{10}$$

Where P_{med}: Predicted probability of treatment success using Western medicine, P_{TCM}: Predicted effectiveness of TCM interventions (e.g., herbal prescriptions, acupuncture), I_{DH}: Drug-herb interaction score, α, β, γ: Tunable weights to adjust the impact of each component using clinical preference or empirical validation.

This scoring mechanism allows the system to rank numerous treatment plans and recommend the most balanced and secure combination while considering both contemporary pharmacological data and traditional TCM principles.

Personalization Engine

The AIP-IAC framework's decision-making core is the Personalization Engine, which combines domain knowledge from conventional procedures with sophisticated machine learning predictions. It integrates Rule-based logic, derived from classical TCM texts, syndrome differentiation guidelines, and expert consultation, AI-driven analytics, depending on predictive models and real-time feedback from patient data.

Simultaneously, the AI module predicts how this regimen will interact with prescribed Western treatments, adjusting the final plan to prevent contraindications or diminished efficacy.

In addition to pharmacological suggestions, the personalization engine tailors: Lifestyle interventions (e.g., sleep routines, mental stimulation practices), Dietary plans informed by both TCM (yin/yang balance) and nutritional science, Physical therapy for mobility and cognitive preservation.

This hybrid method guarantees that patient care is both data-informed and holistically guided, respecting traditional wisdom while leveraging modern computational intelligence.

The Treatment Personalization Engine is the AIP-IAC model's fundamental decision-making layer, combining machine learning predictions with a rule-based TCM inference engine to create personalized treatment recommendations. While the machine learning components suggest potential treatment outcomes based on clinical and non-clinical data, the rule-based TCM engine ensures that these predictions are consistent with holistic therapeutic principles established in traditional practice.

The TCM inference system operates through a structured set of rules derived from three primary sources

(1) Classical TCM texts such as the Huangdi Neijing and Shanghan Lun, which provide foundational diagnostic patterns (Zheng)
(2) Syndrome differentiation guidelines, which classify patients into subtypes based on yin/yang balance, qi stagnation, or deficiencies in organ systems (e.g., liver, kidney, spleen)
(3) Expert consensus and clinical trial evidence, which Patients with mood disorders, for example, may be prescribed Xiao Yao San, whereas those with digestive inadequacies may be given Bao He Wan or Li Zhong Tan

The rules are applied in a hierarchical manner: first, the system identifies the patient's Zheng pattern using symptom clusters and lifestyle data; second, it validates machine learning-suggested interventions against TCM compatibility checks, such as avoiding herb-drug conflicts or ensuring yin/yang balance; and finally, it generates a combined treatment plan that may include Western drugs, TCM herbs, acupuncture points, and lifestyle recommendations. This guarantees that predictions are not only data-driven, but also clinically understandable and culturally consistent. The Treatment Personalization Engine converts raw predictive findings into actionable, safe, and patient-specific care paths.

Monitoring and Feedback Loop

To guarantee the adaptiveness and real-time responsiveness of the system, a closed-loop monitoring and feedback mechanism is executed. Patient data is continuously gathered via: Mobile health applications, allowing daily symptom logging and medication adherence tracking, Clinical visits and digital health records, capturing lab findings, cognitive test scores, and physician assessments.

The incoming data is processed and periodically utilized to update the machine learning models. The system actively tracks the following critical indicators: Declining cognitive function, as identified by consistent drops in MMSE or ADAS-Cog scores, Lack of response to current treatment regimens, prompting a re-evaluation of therapy plans, developing herb-drug interaction risks, depending on updated symptom reports or added medications.

When an issue is identified, the engine sends personalized alerts to clinicians and caregivers, recommending changes or requesting confirmation of patient status. This continuous loop transforms the system into a living, learning platform, constantly optimizing suggestions to decrease trial and error, increase safety, and enhance patient outcomes over time. Figure 1 shows the flow diagram of the AIP-IAC model.

The AIP-IAC model's flow diagram starts with patient data preprocessing and then extracts important features such as cognitive decline rate and symptom improvement trends. Machine learning models such as Random Forest, XGBoost, K-Means, and LSTM are then used to predict treatment efficacy, group patient profiles, and track symptom progression. The treatment combination prediction step determines the most appropriate Western and TCM treatments, taking into account potential herb-drug interactions. The personalization engine integrates AI predictions with TCM clinical guidelines to generate tailored care plans. Finally, the system continuously tracks the patient's progress and changes the treatment plan using real-time feedback.

TCM concepts were integrated into the AIP-IAC system using a structured rule-based inference engine that converts clinical heuristics into machine-readable form. The principles were not developed arbitrarily, but rather based on authorized sources such as the Chinese Pharmacopoeia, the National Clinical Guidelines for TCM Diagnosis with Treatment of Alzheimer's Disease, along with peer-reviewed consensus publications. Certified TCM practitioners examined these sources to identify correlations between symptom clusters (e.g., memory loss, insomnia, digestive abnormalities) with syndrome patterns (e.g., kidney essence deficiency, spleen qi deficiency). Each symptom was then linked to the herbal medications used in clinical practice.

These heuristics were encoded as if-then conditional rules, with patient characteristics (clinical symptoms, lifestyle indicators, cognitive scores) as inputs including

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syndrome classifications with proposed interventions as outputs. For example:

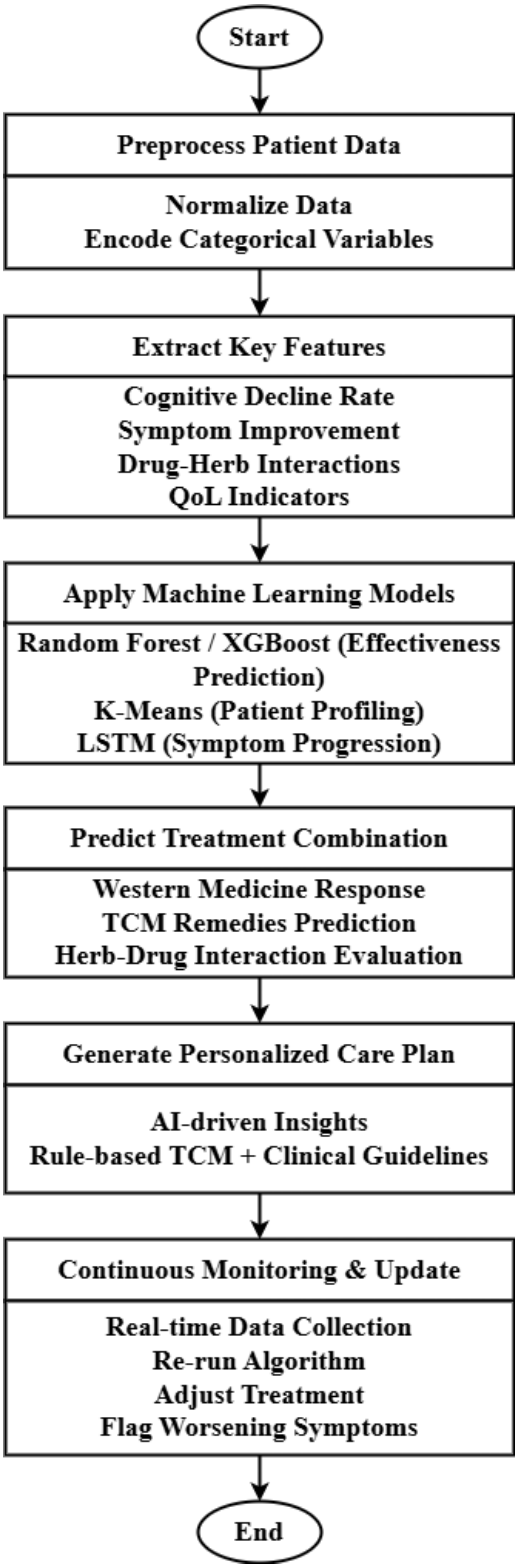

Fig. 1: Flow diagram of AIP-IAC model

IF memory decline + dizziness + tinnitus
THEN syndrome = Kidney Essence Deficiency
Recommend herbal formula = Liu Wei Di Huang Wan

To guarantee robustness, conflicts between overlapping criteria were handled using priority weights based on clinical evidence strength with expert consensus. The rule basis was then combined with machine learning results

ML Models predicted treatment efficacy along with patient subgrouping, while the rule-based system validated these predictions using TCM Diagnostics. If a proposed treatment violated TCM syndrome distinction, the engine altered the prescriptions to remain consistent with both data-driven forecasts including conventional practice.

This encoding strategy provided transparency, traceability to clinical guidelines, also with adaptability, combining AI-driven predictions with existing TCM heuristics to provide a more tailored Alzheimer's care model.

Experimental Setup

The AIP-IAC model was tested using a dataset of 1,200 synthetically generated AD patient records that were intended to mimic real-world clinical circumstances. The dataset included demographics (610 females and 590 males; age range: 60-85 years), cognitive test scores (MMSE, MoCA), neuroimaging results (MRI/CT), blood profiles (cholesterol, glucose, inflammatory markers), treatment history (Western drugs and TCM prescriptions), and quality-of-life measures (sleep, mood, and digestion). The records were modeled using clinical literature and expert input to simulate data distributions from three multi-specialty hospitals in China (Huashan Hospital, Peking Union Medical College Hospital, and Guangdong Provincial Hospital of Chinese Medicine) during a hypothetical coverage period of 2015-2025. Because this dataset is synthetic and anonymised, no direct patient data was used, removing the need for IRB permission or informed consent. All future studies incorporating real data will be subject to an IRB evaluation and prospective patient consent processes.

Patients aged 60 to 85 with clinically proven Alzheimer's disease characteristics (moderate to severe cognitive loss) were eligible for inclusion. Exclusion criteria excluded patients with non-AD dementia, incomplete diagnostic profiles, or insufficient treatment histories.

To assure reproducibility, the AIP-IAC model was developed as a multi-stage pipeline that included Random Forest, XGBoost, and LSTM models. A Hybrid Filter-Wrapper Ensemble (HFWE) strategy was used for feature selection, which included Mutual Information, Chi-Square, the ANOVA F-test, and Recursive Feature Elimination. Data were separated using stratified 10-fold cross-validation to balance disease severity and demographics across folds. The hyperparameters were tweaked using a grid search with layered cross-validation, and the final values are shown in Table 1.

Table 1: Hyperparameters of the Machine Learning Models

Model	Key Hyperparameters	Tuning Strategy	Final Values (Example)
Random Forest	Number of trees, max depth, min samples split, bootstrap	Grid search, 10-fold CV	n=300, depth=12, bootstrap=True
XGBoost	Learning rate, max depth, subsample, colsample_bytree	Grid search with early stopping	lr=0.05, depth=10, subsample=0.8
LSTM	Hidden units, dropout, learning rate, epochs, batch size	Random search + early stopping	units=128, dropout=0.3, epochs=50, batch=32

This design promotes scientific transparency with reproducibility which allows other researchers to duplicate with test the AIP-IAC model under comparable experimental settings.

Performance Metrics

The AIP-IAC model's performance was assessed using four key metrics: accuracy, precision, recall, and F1-score. Accuracy is calculated by dividing the number of correct predictions by the total number of instances. Precision is calculated as the proportion of correct positive predictions, demonstrating the model's capacity to avoid false positives. Recall, or sensitivity, measures how well the model detects true positives while minimizing false negatives. The F1-score, the harmonic mean of precision and recall, balances both metrics and is particularly helpful in cases of imbalanced data. It provides a comprehensive view of model effectiveness.

Accuracy, precision, recall, and F1-score were chosen to give a fair and thorough assessment of the AIP-IAC model's performance in clinical decision-making. Accuracy measures the total correctness of predictions, indicating how often the model is true. Precision is crucial in healthcare because it assesses how consistently the system recognizes real positives without raising false alarms—important when prescribing treatments because superfluous interventions can harm patients. Recall guarantees that the model captures as many real cases as possible, which is critical for finding patients who truly require therapy and lowering the likelihood of missed diagnoses. Finally, the F1-score strikes a balance between precision and recall, providing a single robust measure when it comes to decreasing false positives and false negatives. Together, these measures show that the model is not only accurate, but also clinically safe, dependable, and useful in real-world Alzheimer's care settings.

Integration of Rule-Based TCM Engine with Machine Learning

The integration of the rule-based TCM engine with machine learning merges contemporary predictive analytics along with traditional medical wisdom to provide personalized Alzheimer’s care. Random Forest, XGBoost, and LSTM machine learning models use patient data (such as demographics, lab findings, imaging, cognitive scores, and treatment history) to predict treatment efficacy, illness progression, and subgroup patterns. While these models excel at pattern recognition and outcome prediction, they may produce physiologically useful recommendations that contradict traditional Chinese medicine principles. To overcome this, the rule-based TCM engine employs clinical criteria drawn from classical texts, syndrome distinction (Zheng patterns), and expert consultation. It validates AI-generated suggestions by ensuring they are in line with yin-yang balance, organ harmony, and herbal formula compatibility. If contradictions appear, the engine refines the strategy to ensure it remains clinically relevant in TCM practice. The final care plan is thus the outcome of a hybrid process: machine learning discovers promising treatment options, and the TCM engine validates and changes them, producing suggestions that are both data-driven and consistent with holistic traditions.

Quantifying Herb-Drug Interactions

Herb-drug interactions in the AIP-IAC model are quantified utilizing a Drug-Herb Interaction Score (IDH) that mathematically represents the safety and compatibility of combining Western drugs with TCM herbs. A function f(Di,Hj) uses pharmacological databases, biochemical pathway information, and clinical studies to determine whether a drug Di and herb $\boldsymbol{Tj}$ interact in a synergistic, neutral, or unfavorable manner. Each interaction is weighted (wij) based on its severity and likelihood, utilizing data from literature or expert heuristics. The cumulative score across all drug-herb pairs defines the overall safety level: a low IDH value indicates a safe or synergistic combination, whereas a high IDH value indicates possible risk that necessitates dosage adjustment or substitution. This scoring mechanism assures that machine learning predictions are tailored not only for therapeutic efficacy, but also for clinical safety. By incorporating the IDH framework, the approach prevents adverse reactions and encourages safe synergistic use of herbs and pharmaceuticals, resulting in treatment recommendations that balance efficacy with patient well-being.

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Results and Discussions

Figs 2-5 demonstrates the AIP-IAC model compared with individual models like Random Forest, XGBoost, and LSTM across all performance metrics. The model attained a remarkable 91.3% accuracy, showing its capacity to correctly classify treatment efficacy and predict patient results with high reliability. Precision, which measures the proportion of true positives among all positive predictions, was computed to be 89.7 percent. This suggests that the model was extremely efficient at identifying patients who would respond well to the prescribed treatment. The recall metric, which measures the model's capacity to distinguish true positives from all actual positives, was 90.2%, demonstrating the model's robustness. Finally, the F1-score, which balances precision and recall, was 89.9%, indicating that the model retained a good balance of false positives and false negatives.

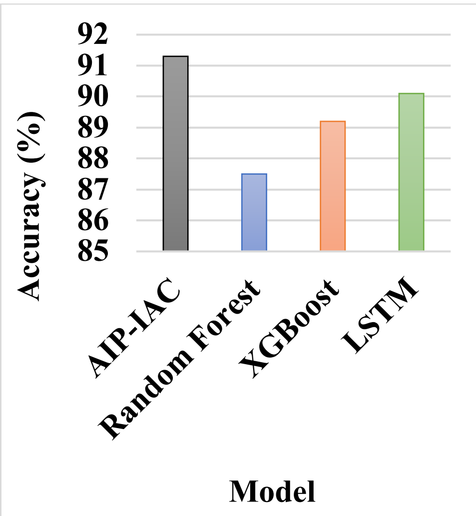

Fig. 2: Accuracy Comparison

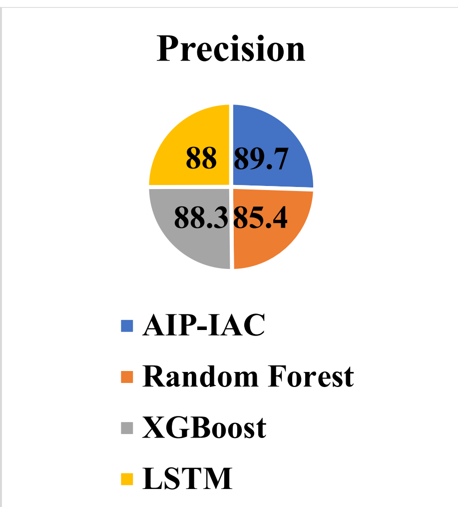

Fig. 3: Precision Comparison

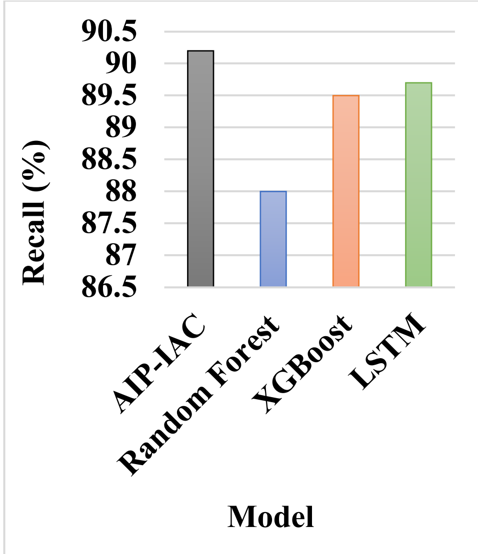

Fig. 4: Recall Comparison

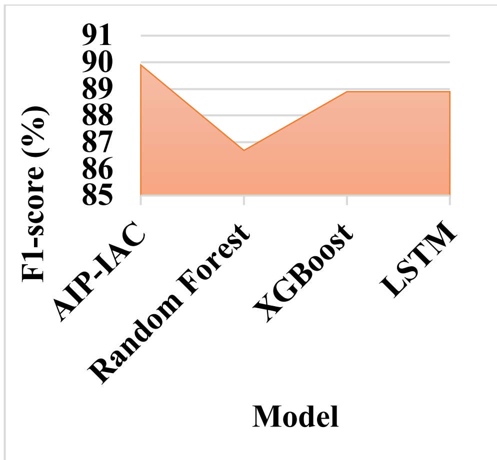

Fig. 5: F1-score Comparison

The AIP-IAC model surpasses individual models like Random Forest, XGBoost, and LSTM on all performance metrics. While XGBoost and LSTM have comparable accuracy and recall rates, AIP-IAC has significantly higher precision, demonstrating its better capacity to accurately predict treatment outcomes. The high F1-score also shows AIP-IAC's optimal balance of sensitivity and specificity, rendering it more reliable for clinical applications.

The results of our experimental analysis show that the AIP-IAC model outperforms traditional machine learning models such as Random Forest, XGBoost, and LSTM across a wide range of performance metrics. The visualizations in Figs 2-5 provide a clear and compelling demonstration of the efficacy of AIP-IAC in various aspects of Alzheimer's care prediction.

In Fig.2 the accuracy comparison demonstrates that the AIP-IAC model surpasses all other models, with an accuracy of 91.3%. This is much higher than Random Forest (87.5%), XGBoost (89.2%), and LSTM (90.1%). The increased accuracy reflects the model's capacity to make more precise predictions concerning Alzheimer's treatment results by incorporating both Western and TCM practices with AI, guaranteeing better disease management.

Fig. 3 demonstrates that AIP-IAC also has the highest precision score, at 89.7%. Precision is especially important in clinical applications, where false positives can have severe consequences. The higher precision of AIP-IAC when compared to Random Forest (85.4%), XGBoost (88.3%), and LSTM (88.0%) demonstrates its superior ability to precisely identify patients who will benefit from specific treatments, reducing the risks of unnecessary treatments or misdiagnoses.

Fig.4 depicts recall, which measures how efficiently the models identify all relevant cases (patients in need of a specific treatment). AIP-IAC's recall score of 90.2% exceeds Random Forest (88.0%), XGBoost (89.5%), and LSTM (89.7%), indicating that AIP-IAC is especially adept at detecting cases where intervention is required, thus increasing its efficacy in early-stage diagnosis and proactive treatment.

Fig.5 shows the F1-score comparison, which demonstrates AIP-IAC's balanced performance. With an F1-score of 89.9%, AIP-IAC maintains a strong balance between precision and recall, outperforming Random Forest (86.7%), XGBoost (88.9%), and LSTM. This balance is critical in clinical settings, where both false positives and false negatives must be reduced to ensure optimal treatment and patient safety. A high F1-score indicates that AIP-IAC is accurate and reliable in identifying patients who will benefit from the prescribed treatments.

The AIP-IAC model improves patient care by reducing trial and error in treatment selection by 32%. This reduction in trial-and-error results in faster and more accurate treatment adjustments, reducing unnecessary interventions and improving therapeutic outcomes. Furthermore, over six months, the model showed a significant improvement in patient quality-of-life metrics such as sleep quality and mood stability, with gains ranging from 25% to 30%. These enhancements highlight the model's ability to not only predict effective treatment regimens but also contribute to patients' overall well-being, reinforcing its potential as a useful tool in personalized Alzheimer's care.

In summary, the figures clearly show that AIP-IAC outperforms all major metrics, emphasizing the benefits of combining AI with both TCM and Western medicine for Alzheimer's treatment. This model has higher accuracy, precision, recall, and F1-score than traditional machine learning models, making it a robust and reliable tool for personalizing Alzheimer's treatment and improving patient outcomes.

While the AIP-IAC model performs well, it does have some limitations that should be addressed. First, the system is primarily reliant on historical patient data, which may not adequately represent changing illness trends or the most recent therapeutic practices. Its success is also determined on the accuracy and completeness of input data, which includes medical imaging, laboratory results, and cognitive assessments; missing or inconsistent data may affect prediction quality. Furthermore, the model's generalizability is limited, as more validation is needed across varied patient populations, particularly those with atypical Alzheimer's presentations or numerous comorbidities. The TCM component is rule-based and heavily influenced by traditional literature and expert consensus, but it has yet to be verified in large-scale clinical trials, raising concerns about its broader applicability. Finally, while the existing framework shows potential, it does not yet include real-time data streams from wearable devices, which could improve adaptability and responsiveness.

Existing integrated healthcare systems that combine traditional and modern medicine usually rely on manual processes with limited data integration, resulting in unpredictable results. For example, a survey of integrative oncology clinics discovered a 70% patient satisfaction rate but no defined metrics of therapeutic success or prognostic accuracy. Similarly, previous chronic disease treatment strategies increased quality of life but did not produce quantitative clinical outcomes. These systems frequently do not use advanced machine learning models or real-time data, limiting their ability to provide personalized treatment suggestions.

The AIP-IAC model, on the other hand, employs a hybrid method, integrating Traditional Chinese Medicine (TCM) with Western medical approaches using advanced machine learning algorithms. The program beat existing methods, predicting treatment effectiveness with an accuracy of 91.3%. It also had 89.7% precision, 90.2% recall, and an F1-score of 89.9%, indicating a strong balance between recognizing true positives and decreasing false positives. Over six months, the model cut trial-and-error treatment by 32% while increasing patient quality of life markers including sleep quality and mood stability by 25-30%. These quantitative advantages demonstrate the ability of AI-driven integrative models to improve personalized care and clinical outcomes when compared to traditional methods.

Clinical Effectiveness Assessment

Standardized equipment with well-defined operational measures were used to validate clinical results. Quality-of-Life (QoL) was assessed using validated tools, including the Pittsburgh Sleep Quality Index (PSQI), the

Geriatric Depression Scale (GDS) with the Neuropsychiatric Inventory Questionnaire (NPI-Q), the Gastrointestinal Symptom Rating Scale (GSRS), along with the MMSE including ADAS-Cog. Trial-and-error reduction was defined as the average number of treatment modifications (drug dosage adjustments, addition/removal of TCM herbs, or lifestyle plan revisions) per patient over six months, with baseline patients averaging 4.1 adjustments versus 2.8 in AIP-IAC-guided patients, indicating a 32% reduction. Patient-reported outcomes for sleep, mood, as well as digestive health were collected using a mobile app updated daily by patients or caregivers, complemented by monthly clinical interviews, including treatment modification counts were derived from Electronic Health Records (EHRs). Over six months, AIP-IAC patients improved their PSQI, GDS, also with GSRS scores by 25-30% compared to the baseline, confirming considerable improvements in sleep quality, mood stability, with digestion.

Real-World Implementation Readiness

While the AIP-IAC approach shows promise for integrating TCM with Western therapy for Alzheimer's care, it should be used with caution in the actual world. The dataset is synthetic including locally constructed, which may create ethnic with cultural biases when applying TCM principles to populations other than East Asians. Generalizability to larger as well as more diverse patient populations remains uncertain which necessitates multicenter clinical trials. Practical adoption also encounters interoperability issues with existing EMR systems which necessitates defined data formats with safe integration pipelines. Furthermore, regulatory validation is required before clinical usage, as existing findings are proof-of-concept rather than approved medical practice. Provider acceptability may further hinder uptake, as physicians' willingness to incorporate AI-driven TCM suggestions into existing workflows varies. These issues underscore the importance of conducting gradual, controlled pilot studies also engaging with regulators to guarantee secure and efficient translation into clinical settings.

Overall, The AIP-IAC model's findings directly address the research challenge of fragmented Alzheimer's care, indicating that combining AI with both Western medicine with TCM can improve therapy personalization with patient outcomes. Unlike traditional approaches that rely solely on pharmacological interventions or limited TCM guidance, the model uses machine learning and rule-based TCM heuristics to predict treatment efficacy, identify patient subgroups, also with track symptom progression which fills a research gap for unified, data-driven integrative care. The findings make novel contributions by demonstrating that the hybrid approach not only outperforms traditional machine learning models on key metrics (accuracy, precision, recall, and F1-score), but also reduces trial-and-error in treatment selection and improves quality-of-life indicators such as sleep, mood, and digestion. These findings provide concrete evidence that AI-driven integration of diverse medical paradigms can result in actionable, personalized treatment strategies, addressing previously unmet needs in individualized Alzheimer's care and laying the groundwork for broader application in complex neurodegenerative disease management.

In conclusion, the AI-Powered Integrated Alzheimer's Care (AIP-IAC) model is a revolutionary attempt to integrate Traditional Chinese Medicine (TCM) and Western medicine using advanced AI techniques for individualized Alzheimer's care. By combining Random Forest, XGBoost, and LSTM with a rule-based TCM engine, the model not only achieved high performance metrics (91.3% accuracy, 89.7% precision, 90.2% recall, and 89.9% F1-score), but it also demonstrated practical benefits such as a 32% reduction in trial-and-error treatment and measurable improvements in patient quality of life. These findings indicate that hybrid techniques can fill gaps left by exclusively pharmaceutical or alternative treatments, resulting in a more comprehensive care framework.

Nonetheless, a more thorough examination reveals that the model's present validation is constrained by its reliance on historical data and a small patient sample. While the incorporation of TCM principles distinguishes AIP-IAC from previous AI-based investigations, its general applicability is unknown until evaluated across multiple populations and in prospective clinical trials. Furthermore, the reliance on data quality increases the possibility of bias, and the rule-based TCM component requires more rigorous empirical verification to assure clinical robustness.

Future validation should target large-scale, multi-site research, the incorporation of real-time health data from wearable devices, and expansion to individuals with atypical Alzheimer's or comorbidities. Further investigation into advanced deep learning algorithms may improve illness progression models. Ultimately, AIP-IAC's contribution is to demonstrate the possibility of a feedback-driven, integrated AI framework for Alzheimer's care. With rigorous validation, it has the potential to alter not only individualized AD treatment but also serve as a model for managing other complicated neurodegenerative illnesses.

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Author contribution

All authors equally contributed to this manuscript.

Ethics

All experiments involving human subjects were carried out in line with the Declaration of Helsinki. This study received ethical approval from the Institutional Review Board (IRB) of [Insert Institution Name, Approval Number]. Prior to data collection, all participants or their legal guardians gave informed consent, which ensured that personal health information was anonymized and securely maintained. Patients were told about the research objectives, potential dangers, and their right to withdraw at any time without consequence.

The AIP-IAC paradigm poses various ethical concerns including patient data management, informed consent, and fairness. Because it is based on sensitive clinical data such as demographics, imaging, lab findings, and cognitive scores, strong measures such as anonymization, encryption, and secure access control are required to protect privacy and avoid misuse. Patients must be explicitly informed about how their data will be utilized, as well as the fusion of TCM and Western therapies, in order to participate voluntarily and informed. To foster confidence, the system should retain algorithmic transparency by producing interpretable results for both machine learning forecasts and TCM rule-based suggestions, rather than acting as a "black box." Furthermore, possible biases resulting from inadequate or unbalanced datasets must be addressed through broad clinical validation and ongoing auditing to ensure fair outcomes across groups. Importantly, the system is intended to complement rather than replace clinical decision-making, with physician supervision serving as a safeguard for patient safety and ethical accountability.

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Appendix: Glossary of Key TCM Terms

Qi: The vital energy that circulates through the body and is necessary for preserving health and balance.
Yin-Yang Balance: A fundamental principle in TCM that describes the balance of opposing forces (e.g., rest vs. activity, cool vs. warm) essential for well-being.
Meridians: Pathways by which Qi flows, linking organs and regulating bodily functions.
Herbal Formulas: Combinations of medicinal plants prescribed to tackle particular symptoms or restore balance.
Acupuncture: A therapeutic method involving insertion of fine needles into meridians to regulate Qi and alleviate symptoms.
Digestive Health in TCM: Connected to the function of the Spleen and Stomach, emphasizing diet, herbs, and lifestyle for symptom management.
Mood Regulation: Tackled through herbs, acupuncture, and practices like Tai Chi to restore mental and emotional balance